2019

VITAL RATES AND HABITAT SELECTION OF BULL ELK (*CERVUS CANADENSIS NELSONI*) IN SOUTHEAST KENTUCKY

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Digital Object Identifier: https://doi.org/10.13023/etd.2019.460

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VITAL RATES AND HABITAT SELECTION OF BULL ELK (*CERVUS CANADENSIS NELSONI*) IN SOUTHEAST KENTUCKY

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Agriculture, Food and Environment
at the University of Kentucky

By

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2019

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ABSTRACT OF DISSERTATION

Vital Rates and Habitat Selection of Bull Elk (*Cervus canadensis nelsoni*) In Southeast Kentucky

Globally, male ungulate species are heavily managed for their sporting and trophy qualities. North American elk (*Cervus canadensis*) are typically managed using a male-biased harvest regime, placing increased chances of mortality on males in these hunted populations. To manage for trophy quality animals that typically represent older age classes, wildlife managers have implemented many age-biased harvest regulations, including spike-only tags and antler point restrictions. Many of these age-biased harvest regulations have fallen short of their desired goal of producing older bull elk. Consequently, the consensus has evolved to center on an overall reduction in harvest pressure.

The state of Kentucky began an elk restoration project in 1997, with 1,553 elk released through 2002. As with other modern elk restoration projects, the male demographic received little research attention in the years immediately post restoration. The difficult logistics surrounding the transport of adult male elk and the reluctance of source states to part with potential trophy animals, led to few adult male elk receiving tracking collars to monitor this demographic. Hunter success rates indicated a growing male component to this population in light of the lack of a radio-marked cohort. With overall population numbers increasing in step with predictive models, so too did hunting tag numbers and hunting pressure. This rise in hunting pressure likely forced elk to become more cryptic, giving rise to the perception of a decline in the elk population, especially older age class male elk. This research represents the first in-depth look at the survival rates and habitat selection of adult male elk in Kentucky.

Recent improvements in field methodology have allowed for the more efficient acquisition of a robust sample of adult male elk. I conducted a radio-telemetry study of adult male elk within southeast Kentucky to investigate the following: (1) survival and cause-specific mortality factors, (2) survival during the fall hunting period, (3) changes in survival following the implementation of a limited entry area (LEA) enclosing our study area, and (4) the associations of morphometric characteristics with the survival of adult

male elk. Given the lack of information on the habitat use of male elk, a cohort of global positioning system (GPS) equipped elk were captured to investigate: (1) seasonal habitat use of male elk, (2) quantification of availability of male elk in readily viewable habitats, (3) changes to the percent of open land within the fall home range of adult male elk, and (4) the influence of open land on survival rates. To investigate the dispersal of male elk, I compared genetic relatedness to space use. Finally, in an attempt to better understand our existing capture methodologies, I analyzed drug induction and reversal metrics for the immobilization drug Carfentanil citrate.

Survival analysis resulted in a 16.9% (CI = 12.2 – 23.7) three-year survival rate for adult male elk. An improvement in survival rate ($p = 0.077$) was noted after the implementation of an LEA system that limited the number of hunters in the study area. No morphometric characteristics were observed to have an association with survival, indicating that hunters indiscriminately harvest male elk. Predictive, habitat use models for male elk indicated a preference for grass habitats and use of habitats near grass patches. Seasonal variation in habitat use was observed with the greatest daily use of grass habitats occurring in the winter season. Adult male elk selected for open land at greater rates than is available across the study area. Over the course of three hunting seasons, elk were found to reduce their use of open land during daylight hours, and we anecdotally believe this to be a response to hunting pressure. A reduction in survival probability of male elk was directly related to use of open land in the final year of the project. Little home range overlap was observed between related male elk, indicating some level of dispersal and intra-specific competition. Predictive models for Carfentanil immobilization indicated an increase in efficacy of a shoulder injection as opposed to a hindquarter drug injection.

Future management of elk in Kentucky should center on promoting the persistence of healthy grassland areas within the elk restoration zone and meeting hunter expectations. Hunter expectations should be gathered and management tailored to meet their desires and the objectives of the management agency. This research indicates that hunters harvest male elk regardless of trophy characteristics, yet we are not sure of the underlying reasons. The interaction of habitat and survival is complex and further complicated by the reclaimed coal mines that Kentucky elk live upon. Habitat management priorities should focus on a heterogeneous, yet healthy habitat that meets the needs of all species residing on these once-exploited lands.

KEYWORDS: *Cervus canadensis*, elk, Kentucky, survival, resource selection, Carfentanil immobilization

John Tyler Hast

12/05/2019

Date

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By

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DEDICATION

To:

Dr. Dave Maehr, Dr. Tom Barnes and Dr. Bill Silvia

ACKNOWLEDGMENTS

This research project would not have been possible without the selfless contributions of many. Modern research projects, especially those involving the capture of large mammals, have requirements above those that could be achieved alone. I owe a debt of gratitude to all that assisted me on my journey through this project. First, I would like to thank Dr. John Cox for his unwavering support through both my master's and doctoral degrees. His passion for conservation biology is infectious and helped me develop a strong conservation ethic that I rely on daily in my current profession. I would also like to thank Dr. Mike Lacki, Dr. Chris Barton, Dr. Robert Harmon and my outside examiner, Dr. Mats Troedsson, for their willingness to serve on my committee, their guidance, their patience and their exceptional review of this dissertation.

The advice, support and friendship of my fellow graduate students was critical to the completion of this project and to keeping a positive mindset during the rigors of graduate student life. I would like to thank Dr. Britany Slabach for her willingness to dive straight into elk capture, her ability to deal with an occasionally salty elk capture crew, her forgiveness when I accidentally threw a hammer at her and the fresh biscuits and other baked goods that were constantly in the oven. Turns out, she was a crack shot with a dart gun and always willing to wrestle an elk – characteristics that were incredibly valuable to the project. Aaron Hildreth and Wade Ulrey added depth to our capture crew with well-honed field skills and assisted with a large number of captures for this project. Additional thanks must also go to Dr. Sean Murphy and Dr. Ben

Augustine. These two fellows were around for almost my entire trip through graduate school and provided countless hours of field work, statistical advice and a solid example of what hard work can achieve. Thanks must go to the staff of the University of Kentucky's Robinson Forest for housing, support and the use of their shop to keep our field vehicles running. Rounding out the UK crew, I must thank Allison Davis for her statistical guidance and her patient review of my often-unwieldy R code.

I would like to thank the Kentucky Department of Fish and Wildlife Resources as well as the Rocky Mountain Elk Foundation for funding this project. Special thanks must go to the biologists and technicians with the Kentucky Department of Fish and Wildlife Resources for unwavering field support and friendship. Dr. Tina Johannsen, Will Bowling, Dan Crank, Gabe Jenkins, Kyle Sams, Todd Duff, Blake Owens, Bobby Owens and Jayson Plaxico all provided support, advice, mentorship and countless hours in the field. Additionally, Joe McDermott and Caleb Haymes, first with KDFWR and later as fellow graduate students and friends, spent large amounts of time holding elk in sternal recumbancy and finding dead elk in the hills and hollers of east Kentucky. The number of elk caught for various research and elk restoration projects between 2011 and 2014 was staggering and speaks to the professionalism and adaptability of our elk capture crew. Thank you for your support and the trust you placed in me to accomplish this project.

I would be remiss not to thank my parents and grandparents for their support during this project and over the course of my life. When I look back on how the trajectory of my life was set, I must give credit to the influences of summers at Kentucky Lake, weekends at our farm and time spent in the woods with my dad and

grandfather. It took many years to understand how lucky I was to have these people and these places in my life. Finally, I would like to thank my wife who constantly reminds me of the things that can be achieved through hard work and an unfaltering dedication to your profession. Your drive and the work you have done to get to where you are today is inspiring. Thank you for your support, love, friendship and veterinary advice over the years.

My most vivid memories of the last fifteen years of my life are focused in eastern Kentucky, typically in a beat up truck packed to the gills with equipment and manned by a group of people smelling of bear, elk or rain gear that has not been dry in weeks. Usually there is a wheel bearing or u-joint about to blow or it is three in the morning and elk are caught in a corral trap somewhere on top of a snow-covered mountain. We were usually exhausted, beat down from a long hike or tired of seeing the world through the windshield of the above-mentioned beat up truck, but we were always successful and complaints were rare. Those were simpler times, with life based on the number of radio collars left to deploy. I will be forever grateful of the time spent with the folks mentioned above and the work that we accomplished.

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CHAPTER 1. SURVIVAL AND CAUSE-SPECIFIC MORTALITY OF ADULT MALE ELK IN SOUTHEASTERN KENTUCKY

Some data used in this chapter appears in the following publication:

Slabach, B. L., J. T. Hast, S. M. Murphy, W. E. Bowling, R. D. Crank, G. Jenkins, K. L. Johannsen, and J. J. Cox. 2018. Survival and cause-specific mortality of elk (*Cervus canadensis*) in Kentucky, USA. Wildlife Biology 2018:1-9.

Abstract

We captured, collared, and monitored 173 mature (>2.5 years of age) bull elk (*Cervus elaphus canadensis*) in the 16 county Kentucky elk restoration zone to investigate survival, cause-specific mortality, and the influence of bull harvest regulations on age-class-specific survival. Using a Cox regression adjusted for staggered entry, we observed a three-year survival rate of 16.9% (CI 12.2-23.7) between 1 January 2011 and 1 February 2014 and observed annual survival rates for 2011, 2012, and 2013 at 71.2% (CI 60.4-83.9), 44.6% (CI 36.0-55.3), and 54.2% (CI 44.9-65.5), respectively. One hundred and eighteen of 173 (68.2%) collared bull elk died primarily from two causes during the study period: hunting-related deaths (n = 91, 77.1%; harvest n = 79 and wounding loss n = 12), and meningeal worm (*Parelaphostrongylus tenuis*) infection (n = 13, 11.0%). The timing of mortality events was skewed towards the fall hunting season due to the heavy influence of hunter harvest and wounding loss sources of mortality.

In 2013, a limited entry area (LEA) was formed around our main study area to investigate the impact of tag reductions on the survival rates of bull elk. The implementation of an LEA that reduced the number of hunters in our study area in 2013 resulted in an increase in bull elk survival rates across age classes (log-rank test; $p = 0.077$, $\alpha = 0.10$) as indicated by a Kaplan-Meier product limit survival analysis. We therefore

recommend limiting hunter pressure through LEA site-specific tag restrictions as an effective means to improve survival rates of adult bull elk proportionately across age classes. Additionally, we employed a Cox regression to determine if certain morphometric characteristics of adult bull elk increased survival chances during the fall season. When morphometrics were included in the Cox regression, no regressors were significant, indicating that Kentucky elk hunters indiscriminately harvest bull elk >1.5 years old.

Introduction

Regulated hunting of ungulates globally generates income used towards the management and conservation of game and non-game species (Coltman et al. 2003, Festa-Bianchet 2003). In the U.S., male-biased harvesting regimes of ungulates are often the default management strategy and typically lead to higher mortality rates of adult males when compared to non-hunted populations (Geist 1971, McCullough 1984, Milner et al. 2007). The elk (*Cervus canadensis*) of North America and East Asia, and its European and western Asian counterpart the red deer (*Cervus elaphus*), are economically, culturally, and ecologically important ungulate game species to these areas (O'Gara 2002). Elk hunters in the U.S. have demonstrated a willingness to pay more for the opportunity to hunt trophy mature male animals (Fried et al. 1995), which in turn generates substantial revenue for wildlife agencies. Consequently, wildlife agencies frequently use age-biased harvest strategies, including establishment of yearling male harvest quotas and minimum antler point restrictions on older age class males (Boyd and Lipscomb 1976, Bender and Miller 1999) to increase male elk survival, numbers, and trophy-class individuals, and to maintain demographics important for overall population viability.

Wildlife managers have theorized that an increase in the survival rates of older age class male elk will lead to a more synchronized rut (Noyes et al. 1996), improved pregnancy rates (Noyes et al. 1996), and increased calf survival rates (Bubenik 1982, Noyes et al. 1996). Several studies have investigated the impacts of manipulating male elk harvest restrictions to achieve management objectives, but results are mixed. For example, minimum point restrictions that protect younger males (Bender and Miller 1999) delayed harvest for one year in most cases (Biederbeck et al. 2001), and did not increase overall survival or the numbers in the older age classes (Bender and Miller 1999, Biederbeck et al. 2001). Bender et al. (1994) found that accurate hunter identification of male age classes was problematic, ultimately concluding that plasticity in antler growth did not allow for antler measures to be used to place male animals in their appropriate age class. Accurate age identification of male elk via field observation was found to be problematic in Kentucky's recently established elk population (J. Hast, unpublished data), both for hunters and researchers. When antler structure is not well correlated with age, minimum point restrictions tend to skew elk harvest towards individuals that are at or near the antler size threshold for legal harvest, but that are not necessarily within a single age class or even within the younger age classes (Bender and Miller 1999, Forrester and Wittmer 2013, Hewitt et al. 2014). The restriction of male elk tags may instead be a better strategy for proportionally increasing survival in the older age classes (Bender and Miller 1999). Survival and cause-specific mortality, or the potential impacts of harvest strategies that skew mean male age lower in populations of highly gregarious species such as elk has surprisingly been rarely studied (Festa-Bianchet 2003, Milner et al. 2007). Recent improvements in chemical immobilization, animal capture techniques, and radio-telemetry

technology (Murray and Patterson 2006) have made it easier to obtain more statistically robust samples of wild animals than in the past (Murray 2006, Murray and Patterson 2006) and quickly access carcasses to better assess cause-specific mortality (Heisey and Fuller 1985, Murray 2006); thus, allowing researchers new opportunities to test management strategies.

Elk were reintroduced to southeastern Kentucky from 1997-2002, and the population has since grown from its 1,553 founders to an estimated size of 13,000 (Kentucky Department of Fish and Wildlife Resources, unpublished data), the largest in eastern North America. Although much elk research and monitoring occurred during the first decade post-release (Larkin et al. 2001), due to the problematic logistics of translocating older male elk and the reluctance of western elk source states to part with valuable trophy animals, only six adult males were included in these early studies. Even with the lack of monitoring, male elk numbers were anecdotally preceived as healthy and hunter success rates (>60% harvest success) remained high through the early years of regulated hunting that began in 2001.

Adult, male elk have since remained largely unstudied within the Kentucky population despite their economic value. Despite this lack of knowledge, managers have for over a decade implemented harvest restrictions, including antler point restrictions and the allocation of spike-only (one antler point per side) harvest tags, assuming these measures would alleviate harvest pressure on older age classes of male elk (G. Jenkins, Kentucky Department of Fish and Wildlife, personal communication). As male tag numbers steadily increased concurrently with elk population estimates, concerns were voiced about the apparent overharvest of male elk. Anecdotally, elk managers saw this

concern as a reaction to the increased wariness of male elk due to a longer season framework, the nature of Kentucky elk habitat and hunter access to that habitat within the Kentucky elk restoration zone. Further, the lack of radio-marked adult male elk in Kentucky limited the ability of wildlife managers to monitor the effectiveness of harvest regulations. As such, I conducted a radio-telemetry study of adult male elk in southeastern Kentucky to investigate the following survival parameters: (1) annual and three-year survival, (2) cause-specific mortality, (3) survival during the fall hunting period, (4) changes in survival rates before and after the implementation of a limited entry area surrounding or study area, and (5) the impacts of select morphometric characteristics on the survival probability of male elk. We hypothesized that: 1) male survival would be inversely correlated with age class, 2) hunter-related deaths and meningeal worm would be leading causes of mortality, and therefore, most deaths would occur during the fall hunting season, 3) that implementation of the limited entry area would improve the probability of survival, and 4) that traditional hunter-desired morphometric features (e.g. large antlers) would increase mortality risk.

Study Area

The 16,802 km^2, Kentucky elk restoration zone (Figure 1.1) is comprised of 16 counties in the southeastern corner of the state, and borders Tennessee, Virginia, and West Virginia. The elk zone is located within the Cumberland Plateau physiographic region characterized by steep hills of 300-1300m in elevation, deep dendritic drainages, and narrow valleys (Larkin et al. 2001). The dominant plant community was mixed-mesophytic forest, characterized by up to 30 co-dominant trees, including yellow poplar (*Liriodendron tulipifera*), sugar maple (*Acer saccharum*), red maple (*A. rubrum*), American beech (*Fagus*

grandifolia), basswood (*Tilia* spp.), yellow buckeye (*Aesculus flava*), northern red oak (*Quercus rubra*), white oak (*Q. alba*), hemlock (*Tsuga canadensis*), black walnut (*Juglans nigra*), black cherry (*Prunus serotina*), shagbark hickory *(Carya ovata*), and white ash (*Fraxinus americana*) (Wharton 1973). Resource extraction, predominately surface mining for coal, altered ~20% of this region by mountain top removal and valley filling of ephemeral streams resulting in flat to rolling topography (Larkin et al. 2001). Mine reclamation in this area involved planting of native and exotic species through hydroseeding of herbaceous plants and limited hand planting of hardwoods. Common plants used in mine reclamation include Kentucky-31 tall fescue (*Lolium arundinaceum*), bush clover (*Lespedeza* spp.), birds-foot trefoil (*Lotus corniculatus*), crown vetch (*Coronilla varia*), perennial ryegrass (*Lolium perenne*), orchardgrass (*Dactylis glomerata*), black alder (*Alnus glutinosa*), autumn-olive (*Elaeagnus umbellata*), white pine (*Pinus strobus*), and black locust (*Robina pseudoacacia*) (Larkin et al. 2001). The climate in the elk zone was temperate humid continental, with warm summers and cool winters (Hill 1976). Mean annual temperature measured at Jackson, Kentucky, was 13.6°C with an average precipitation total of 122.8 cm (US Climate Data 2019).

Methods

Free-ranging adult male elk ≥ 2 years of age were immobilized using a rifle-propelled dart (Pneu-dart, Williamsport, PA) delivered to the rump or shoulder muscles which contained Carfentanil citrate (Zoopharm, Fort Collins, CO) at a dosage of 0.01-0.02 mg/kg of estimated body weight (Kreeger and Franzmann 1996, Kreeger and Arnemo 2012). Immobilized elk were quickly approached and placed in sternal recumbancy to

reduce the potential for bloating and aspiration of gut contents. A liberal application of ophthalmic ointment was applied to the eyes to reduce corneal dryness and damage, and a blindfold was fitted to reduce visual stressors. Respiration, pulse, rectal temperature, capillary refill time, and mucous membrane color were monitored opportunistically during immobilization. After a local injection of 1ml of 20 mg/ml lidocaine to the mental foramen, one lower incisor (I4) was pulled using a dental elevator for the purposes of later age determination through cementum annuli analysis (Linhart and Knowlton 1967, Fancy 1980). Two year-old male elk darted in the summer were aged by the presence of an erupting I4 tooth. We recorded total body length, shoulder height, hind foot length, chest girth, number of antler points, main beam lengths, length of inside spread, beam circumference, and sword point length for all elk. Any signs of previous injury and capture injuries were noted as well as the animal's overall body condition using a four-point scale (poor, fair, good, and excellent). Captured elk were then fitted with either an 8000 MGU global positioning system (GPS) collar acquiring locations on 2-hr intervals or an LMRT-4 very high frequency (VHF) radio collar (Lotek, Newmarket, Ontario, Canada). Immobilized elk were recovered via a shoulder or hip IM injection of the antagonist Naltrexone hydrochloride at a dosage of 100 mg/mg of Carfentanil delivered. Elk were monitored from a safe distance until they became ambulatory and out of immediate danger of self-injury. Elk capture and immobilization procedures were approved under University of Kentucky IACUC protocol # 2010-0726.

Elk fitted with vhf collars were monitored at least once per week via ground or fixed-wing aerial telemetry, and those elk fitted with GPS collars were monitored twice per week via remote downloading of their location data for import into ArcMap 9.3 (ESRI,

Redlands, CA) for spatial analyses. Elk monitoring was increased to three times weekly during and for approximately one month following the fall hunting season. Mortality signals from elk were investigated within 12 hrs of first detection of a mortality signal, and animals were either submitted to the University of Kentucky Veterinary Diagnostic Laboratory for necropsy or a field necropsy was performed on site. Due to the need for a fresh, well-preserved, brain sample for the definitive diagnosis of *P. tenuis*, all suspected elk exhibiting behavioral abnormalities characteristic of a meningeal worm (*Parelaphostrongylus tenuis*) infection were observed closely and euthanized via gunshot to the thoracic cavity once their body condition and flight response deteriorated. The brains of these individuals were sectioned laterally through the skull and both hemispheres of the brain were formalin-fixed (Olsen and Woolf 1979, Pinn et al. 2013), then submitted to the Southeastern Cooperative Wildlife Disease Study at the University of Georgia for *P. tenuis* confirmation (Bender et al. 2005).

A Cox regression in PROC PHREG (SAS, Cary, NC) adjusted for staggered entry following Allison (2010) was used to estimate overall and annual survival. For overall survival, we chose to include all elk captures after 1 January 2011 and terminated the study on 1 February 2014 to include all parts of the 2013-2014 hunting season. In calculating annual survival (2011-13), we included all elk captured during the capture window (approx. January 1 to August 1) whose fate was known as of December 31 of the same calendar year. Captured elk were entered into the study in a staggered fashion due to the long duration of capture and given a 14-day capture myopathy window; those that died during this window were excluded from the study (n = 2). Cause-specific mortality rates were calculated inside of a Cox regression framework adjusted for staggered entry (Allison

2010) by considering only the specific mortality type of interest and censoring for all others (Pollock et al. 1989a, Pollock et al. 1989b, Webb et al. 2011). Hunting season survival rates were calculated using individuals from across the elk zone and considering all types of mortality events. The fall hunting season runs from approximately mid-September to mid-January and thus we used a timeframe from 1 August to 1 February to encompass the entire hunting season as well as to include the potential for mortality as male elk move and prepare for the rut. Archery wounding loss rate was calculated using the total animals hit by archers divided by the number of wounding loss deaths. All hunters and guides were made aware of our study, thus all wounded study animals were reported and observed daily until death or were deemed sufficiently recovered to resume normal activities. Hunting season survival estimates were calculated using a Kaplan-Meier product limit survival analysis in PROC LIFETEST (SAS, Cary, NC) and stratified by age to investigate age-class-specific survival rates. Age classes were grouped as 2, 3, 4, 5, 6, and 7+, the latter class including elk up to 12 years of age. We compared annual survival curves using the log-rank method with Tukey's adjustment for multiple comparisons (Allison 2010).

We calculated Kaplan-Meier product limit survival estimates from 1 August to 1 February for 2012 (115 tags) and 2013 (65 tags, Figure 1.1) and applied a log-rank test, at an alpha level of 0.1, to investigate differences in survival rates due to implementation of a limited area entry (LEA) regulation that changed the number of tags allocated in our main study area. In this analysis, we considered only mortality events due to hunter harvest and wounding loss while censoring all other sources of mortality (Pollock et al. 1989a, Pollock et al. 1989b, Allison 2010, Webb et al. 2011). Choosing to stratify by age allowed us to investigate age class-specific survival rates, while a log-rank test, using Tukey's

adjustment for multiple comparisons, was used to determine differences in survival curves between age class and years (Allison 2010).

To determine if certain morphological aspects of male elk increased their level of hazard during the fall hunting season, we considered only hunter harvest and wounding loss mortality events between 1 August and 1 February of 2012 and 2013. We used a Cox regression in PROC PHREG (SAS, Cary, NC) to determine if the following seven covariates impacted a male elk's chance of mortality: age, physical condition, total antler points, main antler beam length right, main antler beam length left, inside antler spread, and total antler score.

Results

From 1 January 2011 to 1 February 2014 we captured, radio-collared, and monitored 173 adult male elk. Six elk dropped their collars while alive during the study and were right censored in our analyses since we could not confirm a mortality event once the collar was dropped. We calculated a 16.9% (CI 12.2-23.7%) three-year survival rate for adult male elk (n = 173) over the course of this study. Observed annual survival rates were 71.2% (CI 60.4-83.9%) in 2011, 44.6% (CI 36.0-55.3%) in 2012, and 54.3% (CI 44.9-65.5%) in 2013 (Table 1.1). Adult males were over three times more likely to be killed by hunting-related activities than all other causes combined (Table 1.1); 118 of 173 male elk (68.2%) died primarily from two causes during the study period: hunting-related deaths (n = 91, 77.1%; harvest n = 79 and wounding loss n = 12), and meningeal worm infection (n=13, 11.0%; Table 1.2). Additional elk deaths were attributed to road collisions (n = 4, 3.4%), intraspecific wounding (n = 2, 1.7%), fence entanglement (n = 2, 1.7%), poaching

(n = 1, 0.8%), and euthanasia by agency personnel after being trapped in a mine sediment pond (n = 1, 0.8%). Four other deaths (3.4%) were of unknown cause.

Adult male elk survival rates during the hunting season were 74.6% in 2011, 45.2% in 2012, and 55.0% in 2013 (Table 1.3) when considering radio-marked animals across the elk zone. Using the log-rank test, we found that survival curves only differed between 2011 and 2012 ($p = 0.003$; Table 1.3). No difference in survival was found among age classes. Male elk survival increased from 48.2% (SE = 5.5) in 2012 to 62.3% (SE = 5.6) in 2013 (Table 1.4) after the LEA-based regulatory changes in tag allocation in the Hazard limited entry area (from 115 in 2012 to 65 in 2013) were implemented. A log-rank test using Tukey's adjustment for multiple comparisons revealed differences in survival at $\alpha = 0.10$ level ($p = 0.08$) after implementation of the LEA regulations and when only considering hunter mediated sources of mortality (hunter harvest and wounding loss). Using a Cox regression framework, we found no morphometric covariates, such as antler score or body length, that could be significantly attributed to an increase in the hazard rate for male elk during the hunting season when considering hunter harvest and wounding loss sources of mortality in the Hazard limited entry area.

Discussion

Hunter harvest tends to be the largest factor leading to animal mortality in hunted cervid populations (Ballard et al. 2000, Raedeke et al. 2002, Festa-Bianchet 2003). Bender et al. (2004) observed a yearly survival rate of approximately 0.5 for male black-tailed deer (*Odocoileus hemionus columbianus*) from a hunted population in Washington State. Male white-tailed deer (*Odocoileus virginianus*) survival rates ranged from 0.22 (Van Deelen et

al. 1997) to 0.47 (Nelson and Mech 1986) across the northern tier of the United States. Hunting is also typically the primary cause of mortality for elk populations in North America (Ballard et al. 2000, Raedeke et al. 2002). Western elk survival rates are noted to be 0.6 to 0.9 in hunted populations, when considering both sexes together (Unsworth et al. 1993, Evans et al. 2006). Elk in Michigan, a state with a reintroduced elk herd that is heavily hunted for population control, attributed 58% of their mortality events to legal hunter harvest (Bender et al. 2005). Similarly, in Kentucky, we found hunting was the primary (77.1%) cause of mortality for male elk which had a very low 16.9% three-year survival rate.

Prior to the 2012 fall hunting season, the implementation of a hunting system consisting of six large zones allowed many hunters to congregate in the study area due to the ease of access and an abundance of public land. One hundred and fifteen male elk tags were allocated for Elk Hunting Unit 2 in 2012, which included our main study area (Figure 1.1). Much of the public land within this Elk Hunting Unit was located in the southwest corner. Through observations of hunter numbers, we conclude that all of the 115 hunters pursued elk within or near or study area during 2012, likely causing low survival. In response to a perceived overharvest in 2012, the elk restoration zone was reconfigured in 2013 from 6 large zones into 2 at-large zones containing three limited entry areas in an effort to protect those areas from localized overharvest. The Hazard portion of the study area was mostly encompassed by the new Hazard Limited Entry Area and tags were reduced from 115 in 2012 to 65 in 2013, which likely explains the observed increase in survival (Table 1.4).

Overall, 10.2% of male elk mortality events were attributed to wounding loss by archery hunters; no instances of firearms wounding loss were observed. Although the body of research regarding elk wounding loss rates is minimal, rates observed in this study are similar to that of white-tailed deer wounding rates from archery equipment (Ditchkoff et al. 1998, Kilpatrick and Walter 1999, Nixon et al. 2001). We posit that the early season bow hunt (late September to early October) increased the likelihood of male elk succumbing to infection from wounds to the front muscle masses due to the arrow first having to travel into dirty hide often contaminated with soil and urine from rutting activity. Additionally, at this time of the year daytime temperatures average near 26°C and fly activity is high, resulting in wounds that often fail to heal. All arrows that were recovered from expired animals had expandable blades.

P. tenuis, originally thought to be of serious concern for elk restoration efforts in the eastern United States (Larkin et al. 2001, Larkin et al. 2003a), annually caused 6.4% of elk deaths. Research conducted during early phases of the Kentucky reintroduction implicated *P. tenuis* as a major source of mortality for the younger age classes of elk (Larkin et al. 2003a, Larkin et al. 2003b), yet we observed male elk between the ages of 3-8 succumbing to *P. tenuis*, suggesting that this parasite continues to play an important role in population dynamics of adult male elk. Mortality rates observed for *P. tenuis* in this study were much higher than those observed population wide (0.9%) in Michigan elk (Bender et al. 2005); however, in comparison to Kentucky's recent (1997-2002) reintroduction, Michigan elk have been established for nearly a century. We speculate that natural selection in Michigan may have, over a longer time period, favored elk with stronger immune responses to *P. tenuis* as compared to Kentucky's relatively newer,

perhaps relatively naïve population, a supposition that may be supported by findings from the (2001) reintroduction in Great Smoky Mountains National Park where 48.0% of all mortality events were attributed to *P. tenuis* (Murrow et al. 2009).

A heavy harvest of trophy age male elk has been observed to reduce the recruitment rate of elk by decreasing breeding effectiveness through a reduction in rut synchrony (Ryman et al. 1981, Noyes et al. 1996), although the impacts of a young male demographic in elk populations are not well documented (Milner et al. 2007). Reduced elk recruitment rate due to a low mean male age is very dependent on the bull to cow ratio of the population (Bender and Miller 1999, Bender 2002, Bender et al. 2002a, Allendorf and Hard 2009), which obfuscates comparisons of different elk populations. Squibb (1985) observed a direct impact of sport hunting activity as a disruption to rutting behavior. This occurrence increases potentially confounding causative factors of reduced recruitment or fecundity across harvested populations. Implementation of a male-biased sport hunting regime early after reintroduction can lead to high mortality of younger males that often comprise the majority of translocation stock, which in turn can create a highly skewed female-biased sex ratio (Squibb 1985, Festa-Bianchet 2003). Additionally, rut synchrony, and the subsequent birth synchrony it produces, has the ability to increase the effectiveness of predator swamping and further improve neonatal survival (Sinclair et al. 2000).

The LEA zones implemented and tested in this study have the potential to reduce localized overharvest as well as stave off many of the issues surrounding a low mean age among breeding males. Elk managers consider an overall reduction in tags to be the most effective method at increasing survival rates across age classes (Bender and Miller 1999, Ballard et al. 2000, Biederbeck et al. 2001, Bender et al. 2002b). Hernbrode (1987)

illustrates how a failure in the protection of yearling male elk, prompted Colorado to reduce total male permits to improve trophy quality. A study of male elk in Washington State revealed that although an antler restriction did reduce overall mortality, it did not result in a decrease on the harvest pressure of mature male elk (Bender and Miller 1999), with these conclusions mirrored in an Oregon elk population (Biederbeck et al. 2001). In populations where the majority of mortality events are hunting related, conservative tag numbers will generally yield stable population growth (Ballard et al. 2000) and a more natural age structure (Allendorf and Hard 2009).

Allendorf and Hard (2009) posit that most harvest regulations placed on wild populations lead to a nonrandom take of individuals resulting in what the author's term "unnatural selection." Additionally, the usual adherence to the sustainable yield model takes precedence over genetic concerns (Allendorf and Hard 2009). Allendorf and Hard (2009) continue by listing three genetic consequences of selective sport hunting: (1) an alteration of the natural population structure, (2) a loss of genetic variation, and (3) evolution resulting from selection. Coltman et al. (2003) demonstrated a reduction in body weight and horn size of bighorn sheep (*Ovis canadensis)* over a 30-year period of trophy hunting and found that hunters normally harvest young males with trophy characteristics prior to those rams reaching optimum reproductive age. In the case of the bighorn sheep, the adoption of a full curl restriction can be used to remove harvest pressure from the younger male age classes (Coltman et al. 2003). Allendorf and Hard (2009) suggest that the maintenance of genetic variability could be accomplished by eliminating the selective nature of most harvest regimes in ways that mimic mortality of unhunted populations.

The selective impacts of sport hunting are acknowledged more in Europe than in the United States (Allendorf and Hard 2009) due to the differences in hunting culture. For example, European red deer (*Cervus elaphus*) harvest has risen 400-700% in the last 30 years, but trophy male animals make up only a small percentage of the total harvest (Milner et al. 2006). Milner et al. (2006) credits this to a strong meat hunting culture and the heavy cull of female animals to reduce population density. Allendorf et al. (2008) suggested long-term genetic monitoring as the most effective method for evaluating the influences of selective harvest. Just as a full curl restriction limited harvest pressure of bighorn sheep (Coltman et al. 2003), the best method for reducing the rate of selective harvest across various ungulate species is to limit the overall harvest rates (Allendorf et al. 2008). White-tailed deer managers have frequently employed an antler restriction regime despite the lack of a scientific consensus on the subject (Koerth and Kroll 2010). Given that the antler size of most cervids increases with age, this relationship is often used to set harvest restrictions to limit the take of younger animals (Hewitt et al. 2014). Cornicelli et al. (2011) noted that, when given a variety of regulatory options, hunters chose antler-point restrictions above the other options. A more natural age structure is the byproduct of increased survival rates of younger males, and antler-point restrictions may be influenced by variation in antler size, thus not protecting the entire cohort of young animals (Hewitt et al. 2014). Furthermore, the attempted augmentation of overall cervid population genetics by culling of younger age classes has been shown to be unsuccessful (Koerth and Kroll 2010). Consequently, Koerth and Kroll (2010) suggest cervid management efforts be directed towards improving available nutrition sources, maintenance of a more natural age structure, and proper harvest efforts.

Surprisingly, we found male elk were harvested evenly across the adult age classes, and that antler scores were not predictive of harvest likelihood, thus suggesting that hunters indiscriminately harvested male elk in Kentucky. We posit that plasticity in male elk antler development, a high bull to cow ratio (45:100; D. Crank, KDFWR personal communication), and a hunter-perceived limited opportunity to harvest elk (only 2.4% of elk tag applicants were drawn from 2011-13), could explain our findings. With hunters considering antler morphology an accurate predictor of age (Bender et al. 1994), it is likely that hunting pressure is spread across multiple age classes due to the inaccuracies in field aging North American ungulates. It is especially difficult to field age male elk (Bender et al. 1994), and the lack of a relationship between age or antler size and the likelihood of hunter harvest in Kentucky further demonstrates the difficulty in elucidating the relationship among these factors. We suggest that the indiscriminate harvest of Kentucky elk across all adult age classes has the potential to limit the impact of selective trophy harvest on population dynamics and structure (Festa-Bianchet 2003).

Management Implications

Given the desire to manage male elk numbers at a level that allows for optimum hunter satisfaction and viewing opportunity, it is important for wildlife agencies to understand demographic processes and be able to identify strategies that successfully regulate numbers at desired levels. We found that hunting was by far the largest cause of adult male elk mortality in Kentucky that ultimately contributed to low three-year survivorship. Therefore, it will be imperative for wildlife managers to carefully monitor and regulate annual male elk harvest or risk population declines and decreased hunting opportunities (Clark and Eastridge 2006, Murphy 2011).

Although various methods have been used to regulate male elk harvest, the general strategy of these efforts focuses on reducing hunting pressure so as to increase male elk survival and recruitment into the next age class. We have demonstrated that the formation of LEA zones and a reduction in male elk tag numbers have the ability to increase survival rates proportionately across age classes but will by nature limit hunter opportunity in specific areas that can lead to short-term dissatisfaction of this important stakeholder group. We recommend that additional research characterize hunter expectations for harvest that could better inform regulatory measures designed to best match their needs while ensuring those of other stakeholder groups and long-term species viability.

Acknowledgements

The authors would like to thank the various guides and hunters who assisted with sample collection and made us aware of hunter-harvested animals. Additionally, we thank B. Owens, R. Owens, C. Haymes, and J. McDermott for their assistance monitoring and recovering bull elk during the fall hunting seasons. This research was funded with support from the federal McIntire-Stennis program, Pitman-Robertson (PR) funds administered by the Kentucky Department of Fish and Wildlife Resources, and a Project Acquisition Committee grant through the Rocky Mountain Elk Foundation. Finally, we thank C. Osborne and the other staff of the University of Kentucky Robinson Forest for housing and other assistance during our field stay.

Table 1.1. Three-year (2011-2013) and annual survival and cause specific mortality of adult, male Kentucky elk expressed as a survivorship function derived from a Cox regression modified for staggered entry.

	2011-2013*	2011-2012	2012-2013	2013-2014
% Survival (95% CI)	16.9 (12.2-23.7)	71.2 (60.4-83.9)	44.6 (36.0-55.3)	54.2 (44.9-65.5)
% Mortality				
Hunter harvest	68.6	19.6	43.9	30.6
P. tenuis	22.8	8.5	6.1	4.6
Wounding loss	22.0	0.0	6.8	9.5
Random	15.7	3.3	9.1	9.5
All but hunter harvest	49.2	11.5	20.5	21.9
Censored	6 of 173	0 of 61	2 of 107	4 of 97

* Three-year survival

Table 1.2. Three-year (2011-2013) and annual cause-specific mortality for adult, male elk in Kentucky.

	Jan 2011 - Feb 2014	Jan 2011 - Dec 2011	Jan 2012 - Dec 2012	Jan 2013 - Dec 2013
n (mortality events)	173	61	107	97
Cause-specific mortality				
Hunter harvest	79	11	43	25
Wounding loss	12	0	5	7
P. tenuis	13	5	4	4
Road kill	4	0	1	2
Bull kill	2	0	0	2
Poaching	1	0	1	0
Sludge pond drowning	1	0	1	0
Fence entanglement	2	0	2	0
Unknown	4	1	1	2
Total	118	17	58	42

Table 1.3. Kaplan-Meier estimated survival rates of elk during the fall hunting season across the Kentucky elk restoration zone, 2011-2013. The survival rates below were stratified by age class.

	2011		2012		2013	
Age class	N	% survival	N	% survival	N	% survival
2	5	80.0	13	76.2	7	85.7
3	20	100.0	26	56.1	19	52.6
4	17	76.5	32	31.3	26	50.0
5	12	41.7	22	45.5	17	54.3
6	4	50.0	7	14.3	14	57.1
7+	1	0.0	3	33.3	10	50.0
Overall	**59**	**74.6***	**103**	**45.2***	**93**	**55.0**

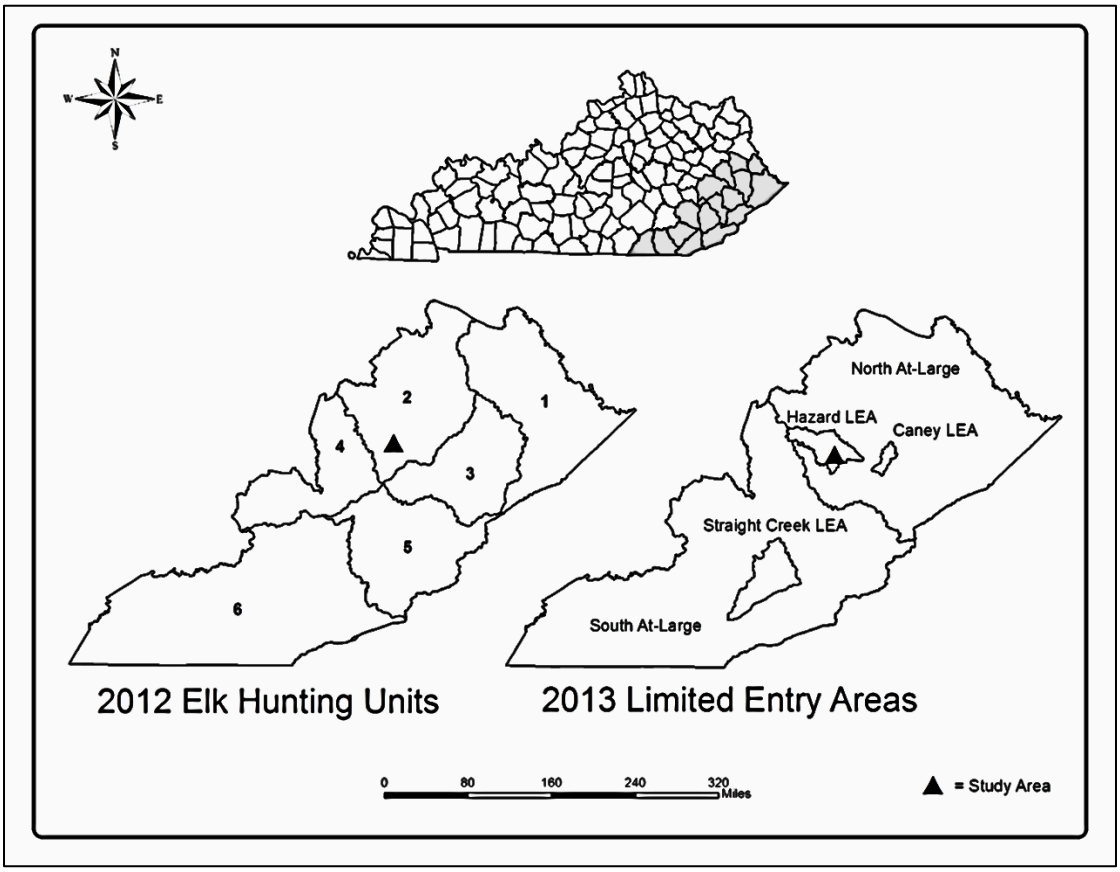
* Survival rates differ between years (P=0.003)

Table 1.4. Kaplan-Meier product limit survival estimates for hunter harvest and wounding loss mortalities in the Hazard, Kentucky study area, 2011-2013. After potential overharvest in 2012, Kentucky elk managers installed a limited entry area surrounding our study area and reduced tag numbers by 30 tags for the 2013 season.

	2012		2013	
Age class	N	% survival	N	% survival
2	13	68.38	7	85.71
3	22	63.31	17	68.75
4	27	34.57	21	56.12
5	19	42.11	12	59.52
6	5	0.00	12	58.33
7+	2	50.00	7	57.14
Overall	88	48.16* (SE=5.47)	76	62.31* (SE=5.75)

* Survival rates differ between years at an alpha level of 0.10 (P=0.077)

Figure 1.1: Adult male elk survival study area (black triangle) within the 16-county southeastern Kentucky elk restoration zone, 2011-2014. Hunting zones were changed in 2013 from six elk hunting units to two at-large areas containing three limited entry areas to minimize overharvest risk in areas with a high density of public land.



CHAPTER 2. RESOURCE SELECTION OF BULL ELK IN SOUTHEASTERN KENTUCKY

Abstract

Fifty adult bull elk were captured and GPS radio-marked between 2011-2013 to investigate resource selection in a study area within the Kentucky elk restoration zone. Using a 90% minimum convex polygon as a home range estimator, 100 pseudo-absences were placed within the home range and regressed against the used points. Elk resource selection was evaluated using logistic mixed-effects regression analysis with multiple habitat characteristics. At each presence and pseudo-absence location, regression fixed effects were extracted from overlapping geographic information system layers for orthoimagery-reclassified habitat (bare, grass or forest), landsat-reclassified habitat (other, developed, barren, deciduous, evergreen, mixed, scrub and grass), topographic position index, slope, distance to road, distance to a 4.04 ha grass patch and area solar radiation index.

Bull elk home range was found to be the largest in the fall of the year, both day and night. Bull elk used grass habitats more so that forest habitats in all seasons except summer day, where forest was selected 47% more than grass. Use of habitat decreased as elk moved away from 4.05 ha grass patches in all seasons except for the winter night season. In all seasonal models, elk selected for areas near the top of the slope as indicated by topographic position index and preferred less steep slopes. The distance from road variable was used in three seasonal models. In the winter day model, selection increased by 7% for every one-unit increase in distance from road, while use decreased by 6% and 4% for summer

day and night, respectively, as elk moved away from roads. Elk managers in Kentucky should focus their efforts on maintaining healthy grassland patches within the existing forested matrix.

Introduction

Animal reintroductions can be fraught with a number of short-term perils (Polziehn et al. 2000, Murphy et al. 2019). Long-term establishment and management of a species can prove equally challenging in maintaining species viability (Frankham et al. 2002, Larkin et al. 2003b). Where species or subspecies have been extirpated, ecological surrogates (e.g. other subspecies) are often used to reestablish biodiversity, ecological function, and provide utilitarian services to humans. In such cases, translocated individuals may have difficulty adapting to their new environment, thereby jeopardizing the success of these projects. Consequently, understanding the dynamic nature between animals and their habitat is critical in such endeavors (Smith et al. 2019).

Morrison (2001) describes habitat simply as "the conditions surrounding the location of an animal." Johnson (1980) defined third order habitat selection as the nonrandom use of habitats within a defined spatial boundary (home range) of an animal. Yet, neither of these definitions take into account the complex decisions an animal must make at different spatial scales (Senft et al. 1987, Fortin 2003). Selection at the home range level may never be truly predictable due to the varying landscape factors at play (Anderson et al. 2005b), and a lack of understanding of the microscale decisions an animal makes as it forages (Senft et al. 1987, Fortin 2003). For example, Senft (1987) posits that herbivores view their food as clustered resources, yet the spatial and temporal scales and resulting coarse resolution of data used in most resource selection studies is often inadequate to

identify important environmental components that affect animal behavior. For example, a hungrier animal may spend a longer amount of time in sub-prime forage to replenish depleted energy reserves before beginning to search for higher quality patches (Fortin 2003).

The eastern elk subspecies (*Cervus canadensis canadensis*) that occupied much of what was historically once a heavily forested eastern North America was overexploited by European settlers and extirpated by the late 1800s. A few decades later, however, small scale elk translocation programs were initiated in a few eastern U.S. states and southeastern Canadian provinces primarily using the Rocky Mountain subspecies (*Cervus canadensis nelsoni*) of elk from western North America. In similar fashion, additional reintroduction attempts were made to establish elk in other parts of its eastern range, particularly during the last 25 years, with subsequent varying levels of population growth (Popp et al. 2014), yet we know little about elk resource selection in this region.

There are many differences in climate, topography, structure and species composition of plant communities between eastern and western elk range in the U.S. For example, elevation plays a key role in habitat selection of western elk, and habitat use varies considerably by season and differing weather conditions (Skovlin et al. 2002). Western elk were observed to prefer a topographic position at the top of the slope regardless of season, due to the advantages related to temperature regulation and anti-predation strategies (Skovlin et al. 2002). While seasonality of a more mild climate and foods are important in eastern elk management, environmental variables such as snow pack depth and presence of large predators are of major concern for elk managers in the western U.S.

(Proffitt et al. 2013), but are not factors in management of eastern elk populations outside the Great Lake states or southeastern Canada.

Elk are highly adaptable and uniquely suited to exploit a variety of resources. Hofmann (1989) considers the division of the ruminant sub-order into two categories, grazers and browsers, as far less specific then necessary. Hofmann (1989) describes ruminant species as existing "within a flexible system of overlapping feeding types" with elk falling in the intermediate range, shifting between grazing and browsing. Consequently, we might hypothesize that translocated Rocky Mountain elk could adapt and exploit the highly productive forests of Southern Appalachia, particularly given the high degree of disturbance caused by logging and surface mining reclamation that have created forest gaps and large expanses of grassland (Larkin et al. 2004, Schneider et al. 2006).

In an established Wisconsin herd, elk located their home range away from wolf territories, while selecting for areas with forbs and grasses (Anderson et al. 2005b). This is in parallel with the recently reintroduced Missouri elk herd which had a high preference for grasslands, forest openings and cool-season food plots installed within the restoration zone (Smith et al. 2019). Overall, Missouri elk preferred to use areas with a sparse canopy cover and areas that had experienced fire recently (Smith et al. 2018). Interestingly, male elk in Missouri and all elk in Wisconsin selected for habitats near roads (Anderson et al. 2005b, Smith et al. 2018). Although neither the Missouri or Wisconsin populations were hunted at the time of the above-discussed research, their selection for areas near roads lies in stark contrast to most western elk herds (Skovlin et al. 2002, Proffitt et al. 2013). It has been readily documented that elk have a negative response to roads and other human

mediated disturbances (Czech 1991, Rowland et al. 2004). With the majority of male elk harvest occurring within the 30-day period overlapping the rut (Slabach et al. 2018), habitat selection during this time will likely be centered on escape cover and avoidance of roads and other hunter-accessible areas (Proffitt et al. 2010). The impacts of hunting and other recreation-based disturbance likely has parallels between the east and the west. Although habitat studies of elk in the western U.S. have suggested a 60:40 ratio of forage to cover (Thomas et al. 1976), little information exists on habitat selection of elk within established herds in the eastern U.S.. The highly variable environments occupied by eastern elk populations warrants investigation into resource use to inform their management (Smith et al. 2018).

Over two decades after reintroduction began, elk in Kentucky have become firmly established with an estimated population of ~13,000 (KDFWR 2015), yet an understanding of habitat use is still important as the population expands its range (Larkin et al. 2004). Additionally, a general understanding of the habitat needs of elk translocated to the eastern United States can be beneficial to other eastern states as they seek to repatriate the species (Popp et al. 2014, Smith et al. 2019). Early releases of elk into the eastern United States often resulted in failure due to inadequate post-release monitoring (Larkin et al. 2001, Larkin et al. 2003b) or release into poor quality habitat (Popp et al. 2014). Early studies of elk in Kentucky included few males, an artifact caused by sources states not wanting to part with mature bulls (Larkin et al. 2004). As the Kentucky elk population grew steadily between 1997-2010, bull elk numbers were perceived as healthy due to consistently high hunter success rates (KDFWR 2015). With tag allotment, season length and subsequent hunting pressure increasing to meet the harvest goals of this expanding population, hunters

and managers began to observe a decrease in the availability of male elk in their traditional foraging habitats. The popular opinion of Kentucky elk hunters at this time was that elk, as grazers, must spend most of their time foraging in open grassland habitats; however, anecdotal observations suggested that bulls were using large forest blocks as sanctuary from hunters and perhaps other human disturbance. We sought to characterize resource use of GPS-collared bull elk by quantifying seasonal and daily habitat use. We hypothesized that male elk in this heavily hunted population would select forests during daylight hours of the hot summer season and during the fall when most elk hunters were active. We further hypothesized that grasslands would be selected over other available habitats at night during all seasons and during daylight hours in the winter season during a period of relative food scarcity.

Study Area

The 16,802 km^2 Kentucky elk restoration zone is currently comprised of 16 counties in the southeastern corner of the state bordering Tennessee, Virginia, and West Virginia. This area was selected due to its limited row crop agriculture and relatively sparse human population, attributes thought to minimize potential human-elk conflict (Larkin et al. 2001). The elk zone is located in the Cumberland Plateau physiographic region characterized by steep hills of 300-1300m in elevation, deep dendritic drainages, and narrow valleys (Larkin et al. 2001). The dominant plant community was mixed-mesophytic forest with up to 30 co-dominant trees, including yellow poplar (*Liriodendron tulipifera*), sugar maple (*Acer saccharum*), red maple (*A. rubrum*), American beech (*Fagus grandifolia*), basswood (*Tilia* spp.), yellow buckeye (*Aesculus flava*), northern red oak (*Quercus rubra*), white oak (*Q. alba*), hemlock (*Tsuga canadensis*), black walnut (*Juglans*

nigra), black cherry (*Prunus serotina*), shagbark hickory *(Carya ovata*), and white ash (*Fraxinus americana*) (Wharton 1973). Resource extraction, predominately surface mining for coal, has altered ~20% of this region by mountain top removal mining practices (Larkin et al. 2001) and leads to the removal of several hundred meters of mountaintop that is later reclaimed into a flat or rolling grassland composed of a mixture of exotic and native herbaceous and woody vegetation. Common plant species used in mine reclamation included Kentucky-31 tall fescue (*Lolium arendinaceum*), bush clover (*Lespedeza* spp.), birds-foot trefoil (*Lotus corniculatus*), crown vetch (*Coronilla varia*), perennial ryegrass (*Lolium perenne*), orchardgrass (*Dactylis glomerata*), black alder (*Alnus glutinosa*), autumn-olive (*Elaeagnus umbellata*), white pine (*Pinus strobus*), and black locust (*Robina pseudoacacia*) (Larkin et al. 2001). The climate in the elk zone is described as temperate humid continental, with warm summers and cool winters (Hill 1976). Mean annual temperature is 13°C with average precipitation of 117 cm distributed evenly over the course of the year (Hill 1976). Mean annual temperature measured at Jackson, Kentucky, was 13.6°C with an average precipitation total of 122.8 cm (US Climate Data 2019).

Methods

Elk were captured and handled under University of Kentucky IACUC protocol # 2010-0726 as follows. Free-ranging adult bull elk ≥ 2 years of age were immobilized using a rifle-propelled 1cc dart (Pneu-dart, Williamsport, PA) containing the immobilization drug Carfentanil citrate at a dosage of 0.01-0.02 mg/kg of estimated body weight (Zoopharm, Windsor, Colorado, USA) delivered intramuscularly to the rump or shoulder. Immobilized elk were quickly approached and placed in sternal recumbancy to reduce the

potential for bloating and aspiration of gut contents. Ophthalmic ointment was applied to the eyes to reduce corneal damage and a blindfold was fitted to reduce visual stressors. Respiration, pulse, rectal temperature, capillary refill time, and mucous membrane color were monitored opportunistically during immobilization. After a local injection of 1ml of 20 mg/ml lidocaine to the mental foramen, one lower incisor (I4) was pulled using a dental elevator for the purposes of later age determination through cementum annuli analysis (Linhart and Knowlton 1967, Fancy 1980). Two-year old bulls darted in the summer were aged by the presence of an erupting I4 tooth.

Captured elk were fitted with an 8000 MGU global positioning system (GPS) collar programmed to acquire a geographical location every 2 hrs (Lotek, Newmarket, Ontario, Canada). Immobilized elk were recovered via a shoulder or hip intramuscular injection of the antagonist Naltrexone hydrochloride at a rate of 100 mg per 1 mg of Carfentanil citrate delivered. We monitored recovering elk from a safe distance until they became ambulatory and out of immediate danger of self-injury. Elk locations were transmitted from the GPS collar to a cell phone modem-equipped desktop computer via text message every 10 hrs. Location error for this model of GPS collar was reported by Augustine et al. (2011).

We employed a supervised classification approach in ArcMap 10 (ESRI, Redlands, California, USA) to classify habitats using a 60 quarter quad section of 2012 orthoimagery obtained from the National Agriculture Imagery Program (NAIP; https://www.usgs.gov/core-science-systems/ngp/tnm-delivery). We used 2012 images because it was the approximate midpoint of the study given that Kentucky orthoimagery is only collected during even years. Habitat was initially classified into three general cover types: bare ground (typically indicative of active mining areas and coal haul roads found

on mining areas within our study area), grassland, and forest. The distance to grass raster was derived by extracting grass patches from the orthoimage reclassification, converting them into polygons, removing grass polygon patches < 4.05ha (10 ac) in size, and calculating a raster of the Euclidean distance from the ≥ 4.05ha grass patches. To further investigate varying habitat types found across the Kentucky elk range, but not identified by the orthoimage reclassification, we reclassified a 2011 National Land Cover Database (NLCD) raster (henceforth landsat) to the following habitat types: other, developed, barren, deciduous forest, evergreen forest, mixed forest, scrub and grass. This landsat raster was used, in an overlapping manner, in conjunction with the reclassified orthoimage as it defined a greater number of habitat types in possible use by elk, yet the authors determined that the precision of its identification of grassland areas was lacking. As such, we felt that the combination of the less precise, but more diversified landsat and the highly precise, yet simple (three habitat types versus eight) orthoimage would best represent habitats important to elk within our study area.

A fifteen quad section of Digital Elevation Model (DEM) raster dataset was downloaded from the Kentucky Geography Network (www.kygeonet.ky.gov) at 1/3rd arc second resolution (approx. 9m). This raster data was used to produce the slope, topographic position index (TPI), and area solar radiation index (ASRI) habitat variables, the last of which was calculated for each season. The Slope tool in the Spatial Analysis toolbox in ArcMap 10 was used to calculate slope. Secondly, the topographic position index was produced using ArcMap 10 per De Reu et al. (2013). The ASRI (watt*hours* meter^{-2}) was calculated with the Area Solar Radiation tool from the Spatial Analyst toolbox in ArcMap 10, using a mean latitude and sky size of 200 cells for each season in year 2011.

Later comparisons indicated that the ASRI produced for each season in year 2011 was equivalent to all other years of the study. Finally, the distance to road variable was derived from a shapefile of state-maintained roads downloaded from the Kentucky Geography Network (https://kygeoportal.ky.gov). A raster of Euclidean distance from major roads was calculated using the Spatial Analyst toolbox in ArcMap 10. All raster layers were aligned and projected to UTM 17N (NAD83) with 9.38m (1/3 arc-second) resolution.

Location files for each elk in the study were combined into a master location file for data processing in R (R Development Core Team 2010). Data processing began by subsampling to one location every 4hrs in a systematic manner to reduce temporal correlation inherent in animal tracking data (Rooney et al. 1998, Börger et al. 2006, Frair et al. 2010). Data processing additionally included the removal of any non-3D fix locations, removal of capture recovery locations defined as those occurring within two weeks of capture, and removal of mortality site locations. We categorized location data into three seasons: winter (1 January to 30 April), summer (1 May to 31 August) and fall (1 September to 31 December), then subdivided each season into diurnal (henceforth, day) or nocturnal (henceforth, night) temporal periods. We delineated these seasonal periods to overlap with observed seasonal activity periods and social behavior of male elk (Killeen et al. 2014a, Benz et al. 2016). The winter (food scarcity) and summer (food abundance) seasons represented typical formation and maintenance of bachelor groups segregated from females and neonates and a general period of body maintenance (winter) or growth (summer) (Killeen et al. 2014a, Benz et al. 2016) while the fall season represented rutting activity (Geist 2002) and periods of hunter disturbance. We classified “day” as one half

hour prior to sunrise to one half hour after sunset to approximate the time that elk would be visible to the naked eye and legal for hunter harvest, and "night" as all hours in between.

Elk resource selection was evaluated using logistic mixed-effects regression analysis. The response variable was elk presence or pseudo-absence. Because animal tracking telemetry cannot report true absences (Manly 2002), pseudo-absences were generated within elk home ranges. For each elk in each season-time dataset, 100 random points were generated within a 90% minimum convex polygon around the elk's actual locations using the R package adehabitatHR (Calenge 2006) allowing us to place pseudo-absences within an area of known use by the individual (Boyce 2006). MCP metrics were chosen due to their robust nature when relocation numbers are low and their frequent use, which allows for comparisons between projects (Harris et al. 1990). The specific 90% MCP size was used due to its representation of a normal level of landscape use (Robertson et al. 1998) while minimizing the inclusion of forays outside of the normally used range (Laver and Kelly 2008), i.e. those extra-range movements that might be included by a larger MCP or utilization distribution.

Varying numbers of relocations per individual are taken into account when applying a mixed-effects regression analysis to the question of resource selection, yet difficulties arise when expectations of independence are applied to pseudo-absences (Fieberg et al. 2010). As such, we applied 100 pseudo-absences to each individually calculated 90% MCP for consistency across individuals (Fieberg et al. 2010, Stewart et al. 2010). We chose not to employ a case-controlled pseudo-absence sampling regime as this requires that pseudo-absences are unused with certainty (Rota et al. 2013). Instead, we settled on using 100 pseudo-absences per MCP where a pilot project indicated an average

home range of 10 km^2, thus placing approximately 10 pseudo-absences per each 1 km^2 of home range space, increasing the probability of these locations being true pseudo-absences (Rota et al. 2013). Elk with ≤ 5 relocations within a seasonal-temporal period, the minimum number of points necessary to construct a minimum convex polygon, were omitted from further analysis (Calenge 2006). After reviewing the number of locations per season for each individual elk, we identified the elk with the lowest number of relocation points, after removing those with <5, as having 23 relocations, enough to justify the asymptotic formation of an MCP (Harris et al. 1990), with the average number of locations per elk per season equal to 289 relocations.

At each presence and pseudo-absence location, regression fixed effects were extracted from overlapping GIS layers for orthoimagery-reclassified habitat (grass, bare, or forest), landsat reclassified habitat (other, developed, barren, deciduous, evergreen, mixed, scrub and grass), TPI, slope, distance to road (droad), distance to grass patch (dgrass), and ASRI for the appropriate season, using the simple extract method from the R package raster (Hijmans 2018). With the determination of a reference level necessary for the regression analysis, the reference level of habitat was set to grass for both the orthoimage and landsat reclassification, because it was anecdotally observed as the most used habitat allowing it to serve as the baseline on which to compare all other habitat types. All continuous covariates were centered and scaled to have a mean of zero and standard deviation of one, but original means and standard deviations of unscaled variables were saved for the creation of predictive rasters later. Individual elk ID was included as a random intercept as illustrated by model 1, below.

Model 1: Y ~ intercept + ortho-habitat + landsat-habitat + TPI + slope + droad

+ dgrass + ASRI + (1|ID)

Model 1 includes random effects coupled with an unbalanced design with the individual elk as the sample unit (Gillies et al. 2006). This allows for the population-level results to remain unbiased from the variation inherent in the number of location data points per individual elk (Gillies et al. 2006). Finally, a logit transformation of the dependent variable, in our case used and pseudo-absences, was necessary to model the response as a linear function of the covariates.

To test for multicollinearity, first a scatterplot matrix of the covariates was visually inspected for correlations using the pairs.pannels function of the package psych (Revelle 2018). Then we calculated variance inflation factors (VIF) using the vif function in the car package (Fox and Weisberg 2011). We examined VIF values following the suggestions of O'brien (2007) and removed covariates with excessive multicollinearity. A visual inspection of the covariate scatterplot matrix revealed no strong correlations among variables, and VIFs of all covariates indicated a lack of multicollinearity (O'brien 2007). Therefore, no covariates were removed from the full model due to multicollinearity. The top model was selected using Akaike's Information Criterion (Akaike 1973, Symonds and Moussalli 2011). AIC allows researchers to compare multiple models while accounting for model uncertainty (Symonds and Moussalli 2011). Our top model was selected as the model with a ΔAIC value of 0.00 which represents the model with the fewest covariates that identifies the highest level of variation contained in the model (Boyce et al. 2002). All models with a ΔAIC <2 were considered, but ultimately we chose not to employ any form of model averaging as those models with a ΔAIC <2 are considered equal, with no

advantage arising through averaging (Symonds and Moussalli 2011). The dredge function in the MuMIn package was used to facilitate AIC evaluation (Barton 2018). The top models were then evaluated using the glmer function from R package lme4 (Bates et al. 2015). A predictive raster produced from the top model for each season was built using the predict function in the raster package (Hijmans 2018) to help visually conceptualize the models and illustrate the seasonal differences in the habitat selection of adult, male elk. Habitat types derived from the landsat reclassification were not included in the predictive raster.

Results

We captured 50 adult male elk aged 2-9 (x = 4) between 1 January 2011 and 31 August 2013. The average 90% MCP home range size for adult male elk, built using an average of 289 relocations, varied by season and was statistically different between winter and fall ($p < 0.05$), with the largest home ranges being observed in the fall season, both day and night (Table 2.1). Elk home range was largest (day = 15.1 km^2, night = 15.1 km^2) during the fall season and smallest (day = 11.7 km^2, night = 11.6 km^2) in winter. All habitat variables were only included in the winter day top model while the winter and summer night models used the fewest variables. Bull elk used grass habitats more than forest habitats in all seasons except the summer day season where forest was selected 47% more than grass (95% CI = 35-60%). Top resource selection models (Table 2.2.) for each season included the orthoimage reclassified habitat, landsat reclassified habitat, TPI, and dgrass (Table 2.3). Slope was included in the top model in all but summer models. Distance to road was selected for during the winter day and summer day and night seasons. ASRI was

used in the top model for all seasonal daytime models and also in the fall night model. Only the winter day seasonal model included all of the available habitat variables.

When only considering the variables from the reclassified ortho-image, bare ground was selected for less than grassland for all seasons. Elk selected for bare ground the most during summer nights (OR = 0.53, 95% CI = 0.43-0.64; Table 2.3) and lowest in the winter day season (OR = 0.12, 95% CI = 0.09-0.16). Bull elk selected grassland over forest during all seasons at night (fall OR = 0.54, 95% CI = 0.49-0.60; summer OR = 0.68, 95% CI = 0.62-0.74, winter OR = 0.53, 95% CI = 0.48-0.59). In comparing forest selection to that of grassland, during the winter day season selection for forest was less than grass with forest being selected for at approximately 0.78 times that of grass (OR = 0.78, 95% CI = 0.70-0.86). Bull elk selected forest during the day less than grassland in the fall (OR = 0.93, 95% CI = 0.84-1.03) and more than grassland in the summer (OR = 1.47, 95% CI = 1.35-1.60). When considering habitat variables derived from a reclassification of landsat imagery, most habitat types in most seasons were used less than grass, the reference variable. Adult male elk were most likely to select for space at the top of slope according to the TPI results in all models (Table 2.3, Figure 2.2). On the high end, selection increased 52% (95% CI = 46-58%) for every one unit increase in TPI during the fall day season. At its lowest point of influence, selection increased by 16% (95% CI = 11-20%) for every one unit increase in TPI during the winter night season. Model results indicated a preference for flatter terrain in the fall with selection decreasing by 20% (95% CI = 17-23%) and 18% (14-21%) in the fall day and night seasons, respectively, for every one unit increase in slope.

The refined models for all seasons indicated a selection for space near a grassland (Table 2.3), except for the winter night season (OR = 1.11, 95% CI = 1.04-1.18) where we observed use increasing as distance to grass increases. The odds of selection decreased by between 7% (95% CI = 1-12%) on the low end for the winter day season and 33% (95% CI = 30-36%) on the high end for the summer day season for every one unit increase in the distance from grassland. Elk selected grassland during the summer season, with selection decreasing by 33% (95% CI = 30-36%) and 27% (95% CI = 24-31) for day and night, respectively, as they moved into other habitats. During the fall season, odds of selection decreased by 15% (95% CI = 11-20%) during the day and by 6% (95% CI = 1-11%) at night as you move away from grassland habitat patches.

The distance from road variable was important in three seasonal models, winter day, summer day and summer night (Table 2.3). In the winter day season, selection increased by 7% (95% CI = 1-13%) for every one unit increase in the distance from a road. Alternatively, in the summer day and night season, selection decreased by 6% (95% CI = 1-10%) and 4% (95% CI = 0-8%) for every one unit increase in the distance from a road, respectively. The area solar radiation index (ASRI) was used to predict space use of adult elk in the fall day season with selection decreasing 10% (95% CI = 6-13%) for every one unit increase in the ASRI value. Additionally ASRI was used in the top models for winter and summer daytime models, as well as the fall night model with selection decreasing by between 8% (winter day) and 3% (summer day).

Discussion

We evaluated resource selection by adult male elk in a section of the Kentucky elk restoration zone. The models upheld our hypothesis that elk would select forest over

grassland in the daytime of summer, yet was inconclusive for the fall season due to insignificant covariate values. We hypothesized that adult male elk would select for grass habitats more than forest in the winter, both day and night. This hypothesis was supported as we found that adult male elk preferred grassland more at night than in the day during the winter season. Home range size varied widely among elk in all seasons while the average home range size varied among seasons (Table 2.1). This can primarily be attributed to the number of location points/season/elk with a minimum of five locations required to construct a 90% MCP using the R package adehabitatHR (Calenge 2006). This variation is accounted for in the resource use analysis in two ways: (1) our use of the 90% MCPs coupled with 100 pseudo absence points per MCP and (2) our inclusion of random effects in the final model. The use of a 90% MCP to define that area within which pseudo absence points were generated allows for inclusion of elk with a smaller home range (due to fewer actual points per season) with those having a larger home range and likely more locations per season. As is the case with our data, the inclusion of a random intercept accounts for an unbalanced design while the inclusion of a random effect accounts for the variability among elk within the same season (Gillies et al. 2006). The inclusion of a random effect into an unbalanced design (differing samples per elk per season) allows us to consider the individual elk as the sample unit while ensuring our population level results are uncoupled from the varying number of data points between individuals (Gillies et al. 2006).

Home range size of adult male elk varied predictably by season with the largest home range size occurring during the fall season (Table 2.1). Anecdotally, while observing elk GPS locations, we noticed large shifts and forays outside of the typical summer home

range during the pre-rut period of late August and early September. We attribute these forays to the start of rutting activity, interspecific competition for harem control (Geist 2002) and an increasing level of human disturbance as the fall season progresses. With home range size inversely related to the abundance of necessary resources (Anderson et al. 2005a, Anderson et al. 2005b), we might logically assume that adult male elk would have a smaller home range in the summer and a larger home range in the winter when resources were scarcer. Additionally, there should be a tradeoff between rare, energy-rich food items and other, less valuable yet more common items (Macarthur and Pianka 1966). Instead, we observed similar sized average home ranges in summer and winter, both day and night (Table 2.1).

One explanation of smaller winter home ranges of bull elk could be an increased reliance on grasses that are concentrated on reclaimed mines in the region, whereas browse is more limited and diffuse during winter. Schneider et al. (2006) described a higher frequency of grass and a lower frequency of browse in fecal samples of Kentucky elk in the winter months. This smaller observed winter home range, coupled with the highest selection for open habitats, both day and night, allows us to posit that elk reduce their movements and concentrate on grass consumption, a habitat available in patches throughout the study area. We observed an importance of open habitats as well as an importance of habitats in close proximity to grass across our seasonal models. Additionally, we saw selection decrease as the distance to a grassland increased. Our null hypothesis of an increased use of grass during the winter day season was thus supported.

Although habitat studies of elk in the western U.S. have suggested a 60:40 ratio of forage to cover (Thomas et al. 1976), little information exists on habitat selection of elk

within established herds in the eastern U.S. The highly variable environments occupied by eastern elk populations warrants investigation into resource use to inform their management (Smith et al. 2018). Resource extraction practices in this area have produced large expanses as well as smaller, more patchy sections of open grassland and early successional habitat, allowing for grass availability year round (Larkin et al. 2003a, Larkin et al. 2004, Schneider et al. 2006). Across the Kentucky elk restoration zone, grass represents approximately 6% of the available habitat (Larkin et al. 2003a, Larkin et al. 2004).

Elk display intermediate feeding tendencies and consume an even amount of grass and browse over the course of the year (Hofmann 1989, Cook et al. 1998), yet the proportions vary seasonally across elk ranges in the east (Schneider et al. 2006, Lupardus et al. 2011, Smith et al. 2018). This intermediate level of foraging allows elk to exploit a variety of habitats for the greatest nutritional gains (Cook et al. 1998). Smith et al. (2018) found that nutrition provided from forage openings were heavily used by Missouri elk translocated from Kentucky into a predominately forested landscape. With < 5% open land habitat within the Missouri elk restoration zone (Smith et al. 2019), these forest openings were constructed and maintained via modern agricultural practices (Smith et al. 2018); thus, likely providing a higher quality forage than that of the reclaimed mine sites in Kentucky. The Tennessee elk restoration zone is approximately 12% pasture and reclaimed strip mine grasslands (Lupardus et al. 2011). In the winter months, Lupardus et al. (2011) observed a preference for tall fescue, the most heavily consumed forage species. Our models clearly show the importance of open, grassland habitats during the winter months and mirror those findings in Missouri and Tennessee.

In support of our hypothesis, adult male elk selected forest over grass during the day in the summer but selected grass over forest at night, a likely thermoregulatory response to the heat of summer. Elk seek thermal cover by selecting good canopy cover or through shifting foraging activities to the dark hours of the day (McCorquodale et al. 1986). Kentucky bull elk likely used both of the above strategies during the summer, relying on browse within forests during the day while selecting grass in open habitats at night. In terms of diet, Lupardis et al. (2011) indicated that Tennessee elk shifted their diet to forbs and legumes in the summer months while Smith et al. (2018) observed Missouri elk preferentially selecting for legume-based diet and a reliance on open habitat areas. A diet compositional analysis of Kentucky elk indicated a more balanced diet of grass, forbs, and browse in the summer season (Schneider et al. 2006), aligning with our observations of an increased reliance on forests in the summer. Thermal cover was not found to improve the overall condition of elk in a captive elk study conducted by Cook et al. (1998). Additionally, Missouri elk did not display a preference for thermal cover and the authors postulated that the abundance of thermal cover, in the form of closed canopy forest, allowed Missouri elk to stay in close proximity to thermal cover while using open habitats (Smith et al. 2018). The above theory likely holds true for Kentucky elk given that an elk could use the middle of our largest patch of open land and still be able to seek thermal cover within a short walk.

Interestingly, elk selected areas far from major roads during winter days (OR = 1.07), but selected areas closer to roads during summer nights (OR = 0.96) and summer days (OR = 0.94), according to the top models for those time periods. Roads are important travel routes for Kentucky elk hunters (J. Hast, unpublished data), but elk are capable of

predicting the timing and location of potential human disturbance (Profitt et al. 2009). Kentucky elk may be selecting open habitats furthest from roads during the summer season to avoid human disturbance from recreationists. Elk in the Greater Yellowstone Ecosystem had a similar response to both wolf predation and human disturbance; they actively avoided these dangerous areas during the hunting season (Proffitt et al. 2009) and this may translate to the summer recreation season where ATVs are in common use in and around our study area. During all other time periods of our analysis, distance to road did not appear in the top-ranked model, potentially due to our inclusion of only state-maintained roads. We chose to ignore gravel and other small roads used for resource extraction because we observed that elk quickly became habituated to the constant traffic associated with surface coal mines.

It has been readily documented that elk have a negative response to roads and other human mediated disturbances (Czech 1991, Rowland et al. 2004). Elk within our study area frequently have roads, mining activity and off-road vehicle use occurring within their seasonal home ranges with disturbance previously recorded in our population by vehicles and hunting (Wichrowski et al. 2005). Additionally, during the fall hunting season, roads allow for an increased level of hunting pressure due to the ease of access with many studies showing an avoidance of roads during this time period (Rowland et al. 2004, Proffitt et al. 2013). From an associated study of male elk survival, it was found that annual survival probabilities range between 43% and 70% over the three years that this study took place (Slabach et al. 2018). With the majority of male elk harvest occurring within the 30-day period overlapping the rut (Slabach et al. 2018), it has been observed that habitat selection of western elk during this time centered on escape cover and avoidance of roads and other

hunter-accessible areas (Proffitt et al. 2010). The impacts of hunting and other recreation-based disturbance likely has parallels between the east and the west. Proffitt et al. (2013) identified female elk actively avoiding areas open to hunting and vehicular traffic in the Greater Yellowstone Ecosystem. Within the same western elk population, it was also observed that elk congregation in refugia closed to hunting had the ability to influence harvest-based management strategies (Proffitt et al. 2010), highlighting the need to understand elk habitat use in intensively managed elk populations.

A bimodal pattern of feeding was observed in Kentucky elk by Wichrowski (2005), with activity increasing near dawn and dusk. Most recently, we have come to understand that wildlife respond to human disturbance by increasing their level of nocturnality (Gaynor et al. 2018). This finding could explain the increased level of grass preference during the night hours of the fall season. Additionally, Gaynor et al. (2018) and Stankowich (2008) observed similarities between the impacts of consumptive and non-consumptive users. All-terrain vehicle (ATV) use, both by hunters (consumptive) and by other recreational users (non-consumptive) may partially explain the elk's avoidance of open habitats during the day. An associated study looking at mortality rates of adult bull elk observed high hunting pressure and a low survival rate among elk in the study area (Slabach et al. 2018). This consumptive disturbance, coupled with a high level of recreational ATV use in the summer and fall and warrants further investigation. As ATVs become more pervasive on the landscape, the study of road ecology may necessitate a transition to "trail" ecology.

The avoidance of predators and human disturbance often requires a tradeoff in resource acquisition (Stankowich 2008, Hertel et al. 2016). We observed that this tradeoff

for elk in Kentucky may be minimal due to a heavy reliance on browse, often found in edge and forests during the fall season (Schneider et al. 2006, Lupardus et al. 2011). Furthermore, over the course of this study, only the fall of 2013 saw a poor hard mast crop within the study area. Although the preference for being in proximity to open habitats is clearly indicated, adult male elk in Kentucky may be able to use the nutritional resources of forests while achieving thermal and escape cover in the daytime of the summer and fall seasons.

Sampling bias, as defined by Stuber et al. (2013), occurs when the captured sample poorly represents the population as a whole. The potential for sampling bias will most likely manifest in the particular methodology within a research project (Jennings and Sibinga 2010). During elk capturing, the authors attempted to put the available GPS collars on older bulls according to field ageing techniques. We balanced this with the desire to make sure all available GPS collars were placed on animals by the August 1 capture cutoff required for drug withdrawal times prior to the fall hunting seasons. Our capture season ran from early January to the first of August and our capture methodology had potential to introduce sampling bias during the winter and summer seasons.

We were most effective darting elk in open habitats where elk could be observed from a vehicle prior to stalking. This methodology may have created bias in our dataset by preferentially selecting for elk that prefer open habitats during the winter and summer capture seasons. Other capture methods such as sitting over a bait site or travel route in differing habitats may have resulted in a lower sample size, yet limited sampling bias. These alternative capture methodologies were hindered by a lack of efficiency as well as

the need to keep the capture team in close proximity to the researcher attempting to dart the elk for human and animal safety reasons.

The age spread (2-9 years of age) of male elk in this study were representative of the overall age structure of male elk in Kentucky observed in harvested bulls and an additional study (KDFWR 2015, Slabach et al. 2018). Hunter harvest data can be used as an approximation of the overall age structure due to Kentucky elk hunters lack of discrimination concerning typical trophy characteristics (Slabach et al. 2018). For this reason, we did not include age in the models and chose instead to investigate resource use across all adult age classes. Including age in the models was further complicated by the fact that most elk contributed location data to the seasonal models for more than one year. Our goal was a broad-scale view of adult male elk resource use.

Management Implications

Elk selected for open habitats and proximity to grass during all three seasons. The resource extraction process associated with surface coal mining operations has produced open, grassland habitats in what would have otherwise been a predominately forested landscape (Larkin et al. 2001, Larkin et al. 2003a, Slabach et al. 2018). These novel grasslands were initially identified as being a key to successful restoration of elk into Kentucky (Larkin et al. 2001), and our findings confirm these and the areas of forest in close proximity to them as being important to bull elk. As such, elk managers in the eastern U.S. would be wise to manage and or create forest openings that contain grass and forbs. More specifically, as Smith et al. (2019) and Larkin (2004) concluded, edge habitat is important for elk resource utilization. As grass patches undergo reforestation, this edge habitat will eventually disappear. Elk managers in Appalachia should therefore focus their

efforts on using techniques such as prescribed fire and herbicide treatments to preserve grasslands given their relative importance.

Acknowledgements

This research was funded by grants from the federal McIntire-Stennis program, Pitman-Robertson (PR) funds administered by the Kentucky Department of Fish and Wildlife resources, as well as by a Project Acquisition Committee grant through the Rocky Mountain Elk Foundation. We also thank C. Osborne and the staff at the University of Kentucky's Robinson Forest for housing and assistance during our stay.

Table 2.1. Home range sizes for bull elk GPS radio-marked in southeastern Kentucky by season from 2011 to 2013. We calculated 90% minimum convex polygons in km^2 for each elk within six seasonal data frames: winter day, winter night, fall day, fall night, summer day and summer night.

Season	n	Average 90% MCP	SD	Minimum	Maximum
Winter Day	42	11.7	10.2	0.45	40.21
Winter Night	42	11.6	10.4	0.48	41.49
Fall Day	46	15.1	12.2	0.32	53.19
Fall Night	46	15.4	12.1	0.41	52.84
Summer Day	50	12.4	13.2	0.24	82.13
Summer Night	50	12.3	12.8	0.20	78.81

Table 2.2. Model selection for seasonal habitat use by bull elk within the Kentucky Elk Restoration Zone from 2011-2013. AIC and ΔAIC values were evaluated for each of six seasonal data frames: winter day, winter night, fall day, fall night, summer day and summer night. The top model, identified by ΔAIC, and the best competing model are displayed.

Season	Model	AIC_c	ΔAIC	logLik
Winter Day	Y~habitat+landsat+TPI+dgrass+slope+road+ASRI	16854.8	0.00	-8411.4
	Y~habitat+landsat+TPI+dgrass+road+ASRI	16855.8	0.97	-8412.9
Winter Night	Y~habitat+landsat+TPI+dgrass+slope	16784.6	0.00	-8378.3
	Y~habitat+landsat+TPI+dgrass	16786.1	1.54	-8380.1
Fall Day	Y~habitat+landsat+TPI+dgrass+slope+ASRI	15375.9	0.00	-7672.9
	Y~habitat+TPI+dgrass+slope+ASRI	15376.9	0.98	-7680.4
Fall Night	Y~habitat+landsat+TPI+dgrass+slope+ASRI	15290.8	0.00	-7630.4
	Y~habitat+landsat+TPI+dgrass+slope+road+ASRI	15292.0	1.20	-7630.0
Summer Day	Y~habitat+landsat+TPI+dgrass+road+ASRI	22835.3	0.00	-11402.7
	Y~habitat+landsat+TPI+dgrass+road	22835.9	0.62	-11404.0
Summer Night	Y~habitat+landsat+TPI+dgrass+road	22263.0	0.00	-11117.5
	Y~habitat+landsat+TPI+dgrass+road+ASRI	22263.0	0.01	-11116.5

Table 2.3. Resource use by bull elk in southeastern Kentucky as defined by a generalized linear mixed-effects model for the years of 2011-2013. Coefficients are presented as odds ratios with 95% confidence intervals in parentheses.

	Seasonal Refined Models					
Varaibles	Winter Day	Winter Night	Fall Day	Fall Night	Summer Day	Summer Night
Intercept	3.41 (2.78-4.19)	4.39 (3.58-5.38)	1.78 (1.32-2.4)	2.67 (1.99-3.58)	3.07 (2.57-3.67)	5.60 (4.66-6.74)
Reclass:						
Bare	0.12 (0.09-0.16)	0.19 (0.16-0.24)	0.15 (0.12-0.2)	0.26 (0.21-0.32)	0.46 (0.37-0.56)	0.53 (0.43-0.64)
Timber	0.78 (0.70-0.86)	0.53 (0.48-0.59)	*0.93 (0.84-1.03)	0.54 (0.49-0.60)	1.47 (1.35-1.60)	0.68 (0.62-0.74)
Landsat:						
Other	*0.98 (0.81-1.20)	*1.22 (1.00-1.50)	*1.04 (0.83-1.32)	*1.21 (0.97-1.51)	*0.95 (0.78-1.17)	1.13 (0.93-1.38)
Developed	0.48 (0.33-0.71)	0.52 (0.36-0.75)	0.59 (0.38-0.90)	0.56 (0.38-0.85)	0.23 (0.16-0.33)	0.44 (0.31-0.62)
Barren	0.61 (0.51-0.73)	0.66 (0.56-0.79)	0.81 (0.67-0.97)	0.79 (0.66-0.94)	0.66 (0.56-0.79)	0.54 (0.46-0.63)
Deciduous	0.79 (0.72-0.87)	0.63 (0.57-0.69)	*0.94 (0.85-1.04)	0.71 (0.64-0.79)	0.83 (0.76-0.90)	0.64 (0.59-0.70)
Evergreen	0.76 (0.65-0.89)	0.58 (0.49-0.68)	*0.89 (0.76-1.04)	0.63 (0.53-0.74)	*0.97 (0.85-1.11)	0.66 (0.58-0.76)
Mixed	*0.91 (0.72-1.15)	0.75 (0.58-0.98)	*0.79 (0.61-1.02)	0.69 (0.53-0.91)	*0.92 (0.75-1.14)	0.67 (0.55-0.83)
Scrub	0.85 (0.73-1.00)	0.69 (0.59-0.81)	*1.04 (0.88-1.24)	*0.91 (0.77-1.07)	*1.06 (0.93-1.22)	0.88 (0.77-1.01)
Continuous:						
TPI	1.26 (1.21-1.31)	1.16 (1.11-1.2)	1.52 (1.46-1.58)	1.47 (1.41-1.53)	1.40 (1.35-1.45)	1.44 (1.39-1.49)
Slope	*0.97 (0.93-1.00)	*0.96 (0.93-1.00)	0.8 (0.77-0.83)	0.82 (0.79-0.86)	X	X
Distance to road	1.07 (1.01-1.13)	X	X	X	0.94 (0.90-0.99)	0.96 (0.92-1.00)
Distance to grass	0.93 (0.88-0.99)	1.11 (1.04-1.18)	0.85 (0.8-0.89)	0.94 (0.89-0.99)	0.67 (0.64-0.70)	0.73 (0.69-0.76)
ASRI	0.92 (0.89-0.96)	X	0.9 (0.87-0.94)	0.96 (0.92-1.00)	*0.97 (0.94-1.01)	X
Random effects:						
Variance (SD)	0.39 (0.63)	0.39 (0.62)	0.96 (0.98)	0.95 (0.98)	0.35 (0.59)	0.38 (0.62)

* $\alpha \geq 0.05$

Figure 2.1. Map of the southeastern Kentucky elk restoration zone and study area (crosshatched square) used to investigate bull elk resource selection. The study area matches the extent of the habitat raster layers used in the resource selection analysis.

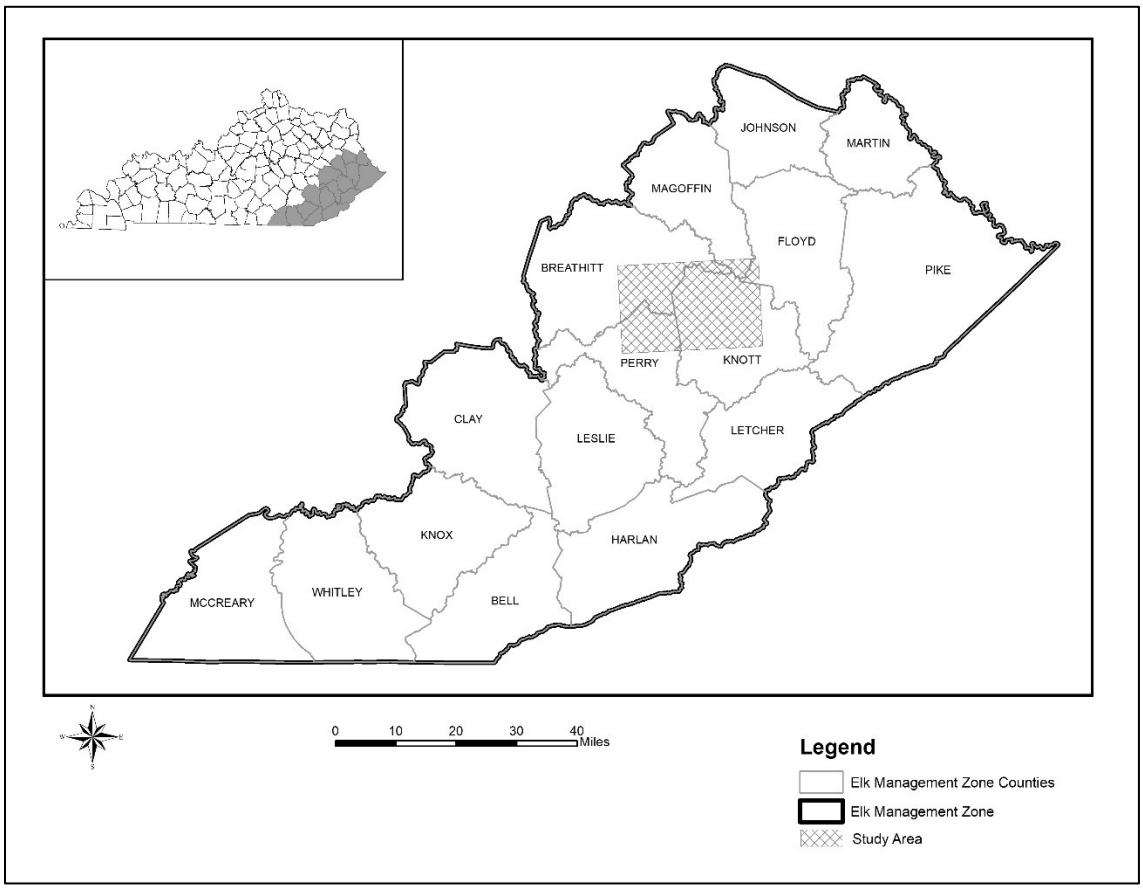


Figure 2.2. Predictive habitat selection rasters for bull elk in the Kentucky elk restoration zone derived form seasonal models for the years of 2011-2013. Each predictive raster was developed using the top habitat selection model for each season.

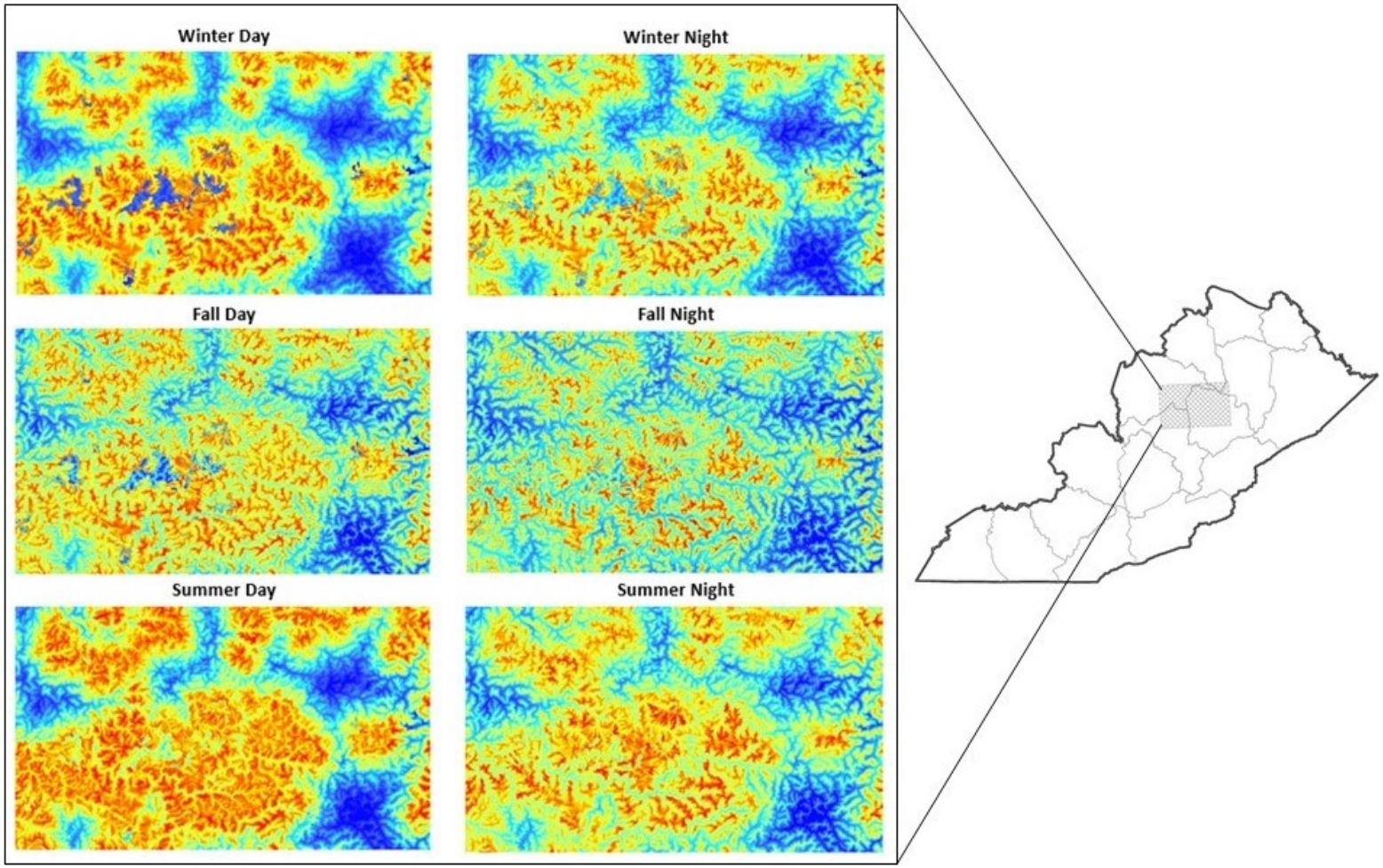
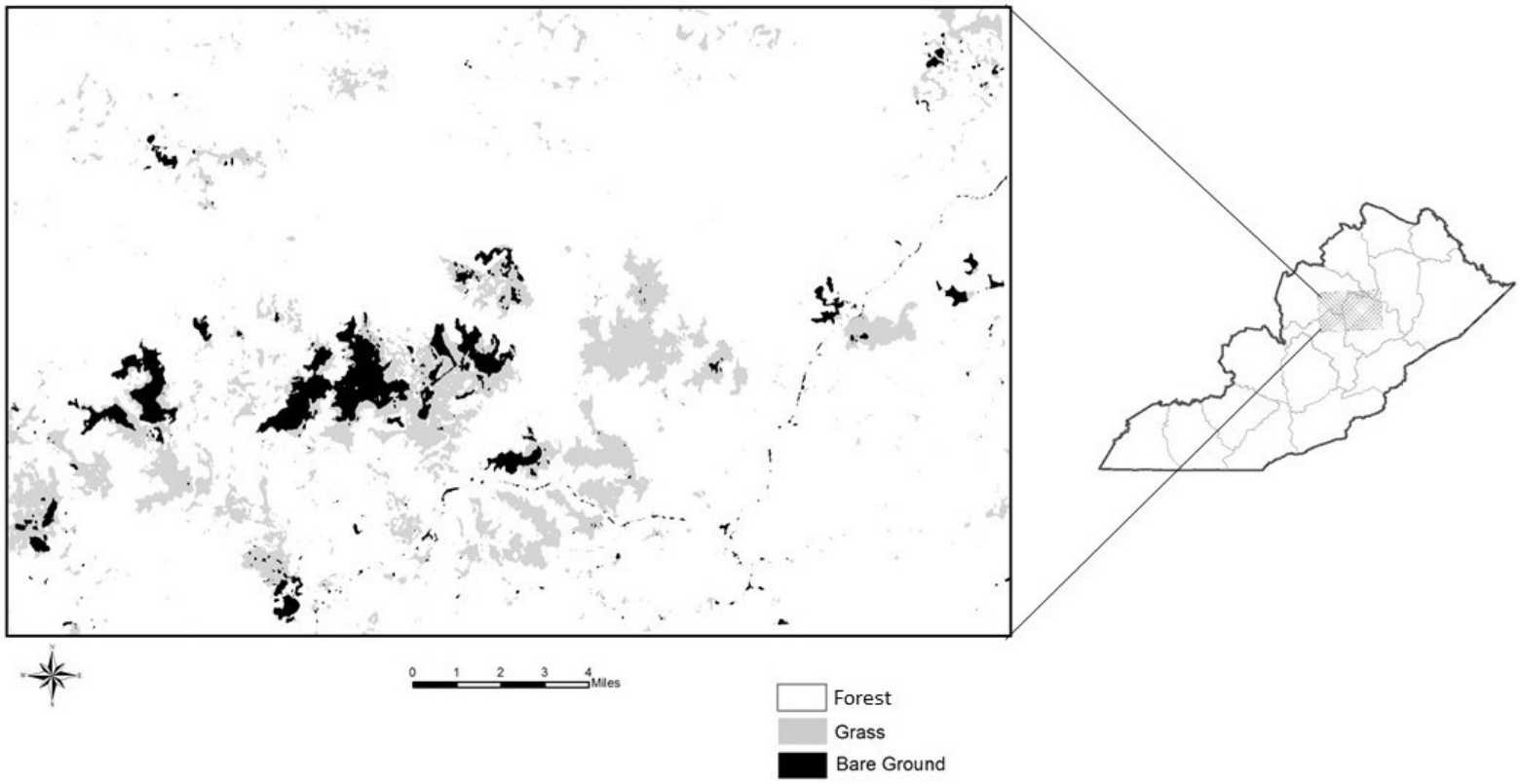


Figure 2.3. Habitat reclassification map of the study area in Eastern Kentucky where GPS radio-marked bull elk were used to investigate resource selection from 2011-2013. Our study area mirrors the elk restoration zone as a whole in that it is approximately 6.8% grassland habitat.



CHAPTER 3. OUT IN THE OPEN: THE RELATIONSHIP BETWEEN CANOPY CLOSURE AND SURVIVAL OF BULL ELK IN SOUTHEASTERN KENTUCKY

Abstract

With bull elk numbers anecdotally perceived to be in decline, we sought to determine if open land inclusion in the core and home range of bull elk influenced survival. Using reclassified orthoimagery, we developed a habitat raster that represented bare ground, grass and forest habitats. After constructing minimum convex polygons to represent the core range (50% MCP) and home range (90% MCP) of bull elk within the Kentucky elk restoration zone, habitat characteristics were extracted. The amount of open land (bare and grass habitats) and age of elk were regressed using a Cox proportional hazards model to investigate the influences of open land on survival. Fifty six percent of radio-marked bull elk died over the three years of this study with annual survival estimated at 76.5%, 23.8% and 68.4%, respectively, in 2011, 2012 and 2013.

Across the study area, open land comprised 9.2% of the available habitat, yet bull elk overwhelmingly included a greater amount of open land in their core (45.1%) and home range (40.6%). Over the three years of this study, we found bull elk to include approximately 50% less open land in both their core and home range when comparing values from 2011 to those in 2013. A Cox proportional hazards model indicated that the percent of open land within the core and home range of bull elk in the fall season across years was not a significant predictor of survival. Yet, when investigating the percent of open land within the core range in 2013, we identified a 37.2% increase in hazard for every one percent increase in open land included in the core range.

Introduction

Elk management in the western U.S. is typically focused on strategies that address 3 key habitat components: nutrition, cover (for security and thermoregulation), and the effects of roads (Lyon and Canfield 1991, McCorquodale et al. 2003, Proffitt et al. 2010, Proffitt et al. 2013, Ranglack et al. 2017, Amor et al. 2019). Western elk management during the fall hunting seasons revolves around hunter access via roads and the protection or establishment of security cover (Lyon and Canfield 1991, McCorquodale et al. 2003, Proffitt et al. 2010, Proffitt et al. 2013, Ranglack et al. 2017, Amor et al. 2019). Following these management priorities, it is well established that elk will select for habitats that minimize security risks, once these pressures are detected by elk (Proffitt et al. 2010, Proffitt et al. 2013). On lands open to hunting, elk were found to select for areas with a greater level of canopy cover (Ranglack et al. 2017), with the assumption that greater canopy cover equates to better security cover. In this same study, Ranglack et al. (2017) defined a security area as that which has greater that 13% canopy cover and at a distance greater than 2,760m from an open road. Even with these observations, elk were also found to be flexible in their use of areas with little or no security cover in western habitats. For example, elk within an arid, shrubland area in Washington state were found to use areas absent of security cover when hunting disturbance was nonexistent (McCorquodale et al. 1986).

Potential shortcomings of this approach to elk management when applied to eastern U.S. elk habitats include: (1) the higher road density in many eastern states compared to the west (Riitters and Wickham 2003), and (2) the existence of ample security cover with much of the eastern U.S. in forested. Elk in most eastern habitats are located within a dense

matrix of roads (Riitters and Wickham 2003) and in close proximity to deciduous and mixed timber stands that could serve as important security cover, yet elk in two unhunted eastern populations (MO, WI) selected for grasses and forbs found in open areas (Anderson et al. 2005b, Smith et al. 2019). Given the disproportionate ratio between open and timbered areas in the east versus the west, one might anticipate that eastern elk could better avoid harvest by using the ample security cover found in the large expanse of habitats with nearly 100% canopy cover; however, this behavior may be offset by a more dense road network and the associated ease of hunter access into elk security cover found in the east.

Male ungulates, in particular, are harvested at greater rates than females within hunted populations and at greater rates than male ungulates from un-hunted populations (Geist 1971, McCullough 1984, Milner et al. 2007). Hunting mortality has a varying role on population demographics of elk in the eastern U.S. and is typically reflective of management goals. For example, researchers in Pennsylvania attributed 10% of mortality events to hunter harvest while managing for population expansion (Banfield and Rosenberry 2015) compared to 58% in Michigan elk, where population numbers are highly regulated (Bender et al. 2005). During a three year study of a heavily hunted population of elk within the study area in Kentucky, researchers identified legal harvest (47.9%) and wounding loss (6.8%) as the top two sources of mortality for bull elk (Slabach et al. 2018). Within eastern elk habitats, little is known about how the inclusion of open habitat within the home range of elk might influence the impacts of hunter-mediated elk mortality.

For example, within the Kentucky elk restoration zone, it has been demonstrated that cow elk mortality rates were determined by hunter access and land ownership (Slabach et al. 2018) and, although they did not consider other habitat variables, anecdotal

observations suggested that the highest levels of harvest took place in a herd that resided largely on public land that contains a large proportion of open grassland. Yet the literature is replete with examples of hunter avoidance by elk. In South Dakota, Millspaugh et al. (2000) observed elk avoiding areas with high hunting pressure and selection of forests that had an increased level of security cover. Elk within the Greater Yellowstone Ecosystem were found to select areas away from hunters to an extent that greatly reduced the number of elk available for harvest and limited the impact of population control efforts via hunting (Proffitt et al. 2010, Proffitt et al. 2013). Interestingly, in the same population of western elk, it was observed that the response to hunting and wolf predation were equivalent (Proffitt et al. 2009). The selection for security cover is a response to the fact that open lands represent a dangerous area for elk during a hunting season, with modern hunting weapons being able to take an elk beyond 300 m (Ciuti et al. 2012, Thurfjell et al. 2017).

Grasslands are not historically common to the Cumberland Plateau of Kentucky (Larkin et al. 2001), yet resource extraction, particularly surface coal mining, has resulted in approximately 6-10% of the Kentucky elk zone being either active or reclaimed mining areas (Plass 2000, Larkin et al. 2001, Cox 2003, Schneider et al. 2006). In a study of the mining effects on reptile hibernacula near the study area, Maigret et al. (2019) estimated that 6.9% of the Cumberland Plateau region of Kentucky had been mined. Reclaimed mine areas (or "minescapes") are commonly reseeded with a variety of species including non-native grasses and forbs, and native woody species (Schneider et al. 2006). Grassland sites, in proximity to elk release locations, were deemed of critical importance to elk restoration success due to their resemblance to western elk habitats in hopes of maintaining strong release site fidelity and reducing human-elk conflict (Larkin et al. 2001). Although not

evenly distributed across the Kentucky elk restoration zone, minescapes do occur in portions of the restoration zone (Larkin et al. 2001), including the study area. One of the seven original release sites used to restore elk to Kentucky lies at the approximate center of our study area and was recognized for its abundance of open grassland habitat (Larkin et al. 2001).

In chapter 2 of this dissertation, I demonstrated that bull elk showed roughly the same selection preference for forest compared to grassland habitats, which I associate with security cover, during the daylight hours of the fall hunting season. Although distance from road was not included in the top model for daylight hours during the fall hunting season, bull elk did select areas away from roads at night in the fall. Topographic position index (TPI) was also strongly influential in predicting bull habitat use in Kentucky (Chapter 2; Table 2.2). Maigret et al. (2019) helped to explain why bull elk prefer to be near the top of the slope with their analysis of mountain top removal mining practices in an around the study area. Mining practices in this area more heavily influenced ridgetop and upper slope positions (Maigret et al. 2019), thus focusing reclamation activities and subsequent grassland areas at the top of the slope. This practice puts the open grassland areas at the top of the slope and likely in the most visible areas (Ciuti et al. 2012), rendering elk more susceptible to hunters practicing spot-and-stalk hunting, the preferred method of hunting elk (G. Jenkins, personal communication). Contrary to western habitats, where an increase in TPI likely puts elk further from the reach of hunters, mining activities across the study area have greatly increased hunter access to ridgetop habitats through the construction of coal haul roads that typically remain in place post reclamation. Collectively, these

landscape conditions and hunter behaviors suggest that elk which spend more time in open areas may be more vulnerable to hunters.

Given the high hunter-mediated mortality rates recently found in this population by Slabach et al. (2018) and the wealth of literature suggesting that forests serve as security habitats (Lyon and Canfield 1991, McCorquodale et al. 2003, Proffitt et al. 2010, Proffitt et al. 2013, Ranglack et al. 2017, Amor et al. 2019), I evaluated the impacts on survival of percent open land at two spatial scales (core area and home range) of GPS-marked bull elk on survival. Specifically, I investigated: (1) the percentage of open habitat within the fall seasonal core area and home range of bull elk compared to that available in the study area as a whole; (2) the change in the percent of open land within adult, bull elk fall core areas and home ranges over the progression of three hunting seasons; and (3) the relationship between percent of open land within the fall core area and home range to survival probability during the fall hunting season. I hypothesized that bull elk would have a greater proportion of open grassland present in their core area and home range relative to the proportions observed across the study area as a whole, and that I would observe less open land inclusion in the core area and home range as the study progressed due to an increase in hunting pressure. Additionally, I hypothesized that bull elk with higher levels of open grassland in their fall seasonal core area and home range would experience lower survival rates due to increased vulnerability to detection and harvest by hunters.

Study Area

The elk in our study occupied a 2,363 km^2 portion of the 16-county Kentucky elk restoration zone in the southeastern portion of Kentucky (Figure 3.1). This area is

characterized by the Cumberland Plateau physiographic region with steep hills of 300-1300m in elevation, deep dendritic drainages, and narrow valleys. The dominant plant community was mixed-mesophytic forest, characterized by up to 30 co-dominant trees, including yellow poplar (*Liriodendron tulipifera*), sugar maple (*Acer saccharum*), red maple (*A. rubrum*), American beech (*Fagus grandifolia*), basswood (*Tilia* spp.), yellow buckeye (*Aesculus flava*), northern red oak (*Quercus rubra*), white oak (*Q. alba*), hemlock (*Tsuga canadensis*), black walnut (*Juglans nigra*), black cherry (*Prunus serotina*), shagbark hickory *(Carya ovata*), and white ash (*Fraxinus americana*) (Wharton 1973). Resource extraction, predominately surface mining for coal, had altered ~7% of this region by mountain top removal and valley filling of ephemeral streams resulting in flat to rolling topography (Maigret et al. 2019) . Mine reclamation in this area involved planting of native and exotic species via hydroseeding of herbaceous plants and limited hand planting of hardwoods. Common plants used in mine reclamation included Kentucky-31 tall fescue (*Lolium arundinaceum*), bush clover (*Lespedeza* spp.), birds-foot trefoil (*Lotus corniculatus*), crown vetch (*Coronilla varia*), perennial ryegrass (*Lolium perenne*), orchardgrass (*Dactylis glomerata*), black alder (*Alnus glutinosa*), autumn-olive (*Elaeagnus umbellata*), white pine (*Pinus strobus*), and black locust (*Robina pseudoacacia*) (Larkin et al. 2001). The climate in the elk zone was temperate humid continental, with warm summers and cool winters (Hill 1976). Mean annual temperature measured at Jackson, Kentucky was 13.6° C, with an average precipitation total of 122.8 cm (US Climate Data 2019).

Methods

Free-ranging adult, male elk ≥ 2 years of age were immobilized using a rifle-propelled dart (Pneu-dart, Williamsport, PA) containing the immobilization drug Carfentanil citrate at a dosage of 0.01-0.02 mg/kg of estimated body weight (Zoopharm, Windsor, Colorado, USA) delivered intramuscularly to the rump or shoulder. Immobilized elk were quickly approached and placed in sternal recumbancy to reduce the potential for bloating and aspiration. Ophthalmic ointment was applied to the eyes to reduce corneal damage and a blindfold was fitted to reduce visual stressors. Respiration, pulse, rectal temperature, capillary refill time, and mucous membrane color were monitored opportunistically during immobilization. Captured elk were fitted with an 8000 MGU global positioning system (GPS) collar programmed to record a location every 2 hrs (Lotek, Newmarket, Ontario, Canada). Error rates for this model of GPS collar were quantified in Augustine et al. (2011). Immobilized elk were recovered via a shoulder or hip intramuscular injection of the antagonist Naltrexone hydrochloride at a rate of 100 mg per 1 mg of Carfentanil citrate delivered. Elk were monitored from a safe distance until they became ambulatory and out of immediate danger of self-injury. Elk capture and immobilization procedures were approved under University of Kentucky IACUC protocol # 2010-0726.

Location files for each elk in the study were first combined into a master file for data processing in R (R Development Core Team 2010). Non-3D fix locations, sites of mortality, and all post-capture locations within the first 14 days were removed. Elk locations during daylight hours from September 1 to October 15, were pulled from the master file to cover the rutting period (Geist 2002, Killeen et al. 2014a, Benz et al. 2016)

and the time period when most bull elk were harvested (Slabach et al. 2018). I considered daytime to be one half hour prior to sunrise to one half hour after sunset to approximate the time that elk would be visible to the naked eye and legal for hunter harvest. Data were then systematically subsampled to one location every four hours with locations occurring at 0900, 1300 and 1700 hours to represent times elk are likely to be in different activity modes (0900 and 1700 represent feeding periods; 1300 represents midday rest period) (Robertson et al. 1998, Rooney et al. 1998, Katajisto and Moilanen 2006), to reduce temporal correlation inherent in animal tracking data (Rooney et al. 1998, Börger et al. 2006, Frair et al. 2010). Three data sets were created based on year of the study spanning 2011-2013. We used a piping function within the packages of plyr (Wickham 2011) and dplyr (Wickham et al. 2018) to ensure that each individual elk had > five relocations each year during the fall season to allow for an asymptotic range estimate (Harris et al. 1990). The R package adehabitatHR (Calenge 2006) was used to calculate 50% and 90% minimum convex polygons (MCP) for each elk in each annual data frame. The core range metric was chosen based on the review by Laver and Kelly (2008), where the 50% MCP was identified as the most frequently cited spatial representation of core range. Home range estimates (90% MCP) were based on the normal use of the landscape (Robertson et al. 1998), with the desire to minimize the inclusion of forays (Laver and Kelly 2008).

A sixty-quarter quad section of National Agriculture Imagery Program (NAIP) orthoimagery was downloaded from the United State Geological Survey Seamless Server (https://www.usgs.gov/core-science-systems/ngp/tnm-delivery) to cover the study area for 2012, the midpoint of the study (Kentucky orthoimagery is only collected on even years). We employed a supervised classification in ArcMap 10 (ESRI, Redlands, California, USA)

to reclassify the orthoimagery into three habitat classes: bare ground (representing active mining areas including roads used for mining purposes and paved roads), grass, and forest. We then generated a 50% and 90% MCP fall seasonal core and home range, respectively, for each elk in each year that was used to clip the habitat reclassification imagery, thereby creating a raster of habitat values of seasonal core area and home range for each individual elk. The values from these rasters were then extracted to determine the quantity of each habitat type within the 50% and 90% MCPs for each elk. We calculated the percent of open land (bare ground + grassland) within each MCP, mean and standard deviation for all three habitat types per year and pooled these data across all years. Variations in mean were visualized using the ggboxplot and ggline functions of the ggpubr package (Kassambara 2019). Normality of data was tested using a normality plot of residuals. An analysis of variance (ANOVA) was performed in R to determine if differences in percent of habitats within MCPs occurred among years. We used a Tukey's test to conduct a post-hoc analysis of the differences between years for both the 50% and 90% MCP data.

We regressed survival against the percent of open land in the 50 and 90% MCP range and age of elk to test whether the amount of open land within these spatial boundaries affected survival. The Surv function in package survival (Therneau and Grambsch 2000, Therneau 2015) was used to build a survival object for later use in the Kaplan-Meier analysis and Cox proportional hazards modeling for pooled data and for an analysis of each year. Kaplan-Meier curves for adult bull elk stratified by year were evaluated using the survfit function of the survival package (Therneau and Grambsch 2000, Therneau 2015). We evaluated differences in survival between years by examining Kaplan-Meier survival curves generated by the ggsurvplot function in the survminer package (Kassambara and

Kosinski 2019) with a log-rank test. A Cox proportional hazards model using the coxph function of the survival package (Therneau and Grambsch 2000, Therneau 2015) was employed to evaluate the influence of the percent of open land within each 50% MCP core and 90% MCP home range on annual and 3-year survival of elk. We evaluated Cox regressions for deviations from the proportional hazards assumptions by plotting survival times against Schoenfeld residuals and using a chi-squared test with the cox.zph function of the survival package (Therneau and Grambsch 2000, Therneau 2015). The results of these Cox regressions were visualized using the ggforest function of the survminer package (Kassambara and Kosinski 2019).

Results

Forty-five (2011 = 17, 2012 = 21, 2013 = 19) adult bull elk equipped with GPS collars were used to examine the influence of open land on survival probabilities. Twenty-six of 46 (56.5%) bull elk died during the 3-year study, including 24 of 26 (92.3%) from hunting-related causes (18 harvested, 6 wounding loss), and 2 that were killed by vehicles. Estimated annual survival of bull elk varied widely from a high of 76.5% (95% CI = 58.7-92.9) in 2011 to a low of 23.8% (95% CI = 11.1-51.2) in 2012 (Table 3.2, Figure 3.3). A log-rank test indicated that the survival probability of elk in 2012 differed significantly ($p=0.003$) from that of 2011 and 2013 (Figure 3.3).

Across the study area, open land comprised 9.2% of the available habitat (Table 3.1) of which 2.4% was bare ground and 6.8% was grassland. When data were pooled across all three years we observed an average of 45.0% (SD = 33.0%) open land included within a 50% MCP core area, and 40.6% (SD = 25.7%) open land within a 90% MCP home range. Differences occurred in mean percent open land in both the 50% and 90%

MCPs across years (Figure 3.2). A Cox proportional hazards model, found to meet proportional hazards assumptions, indicated that the percent of open land within the 50% core and 90% home range MCPs of the pooled cohort during the fall season was not a significant predictor of bull elk 3-year survival probability; however, the percent of open habitat within elk core range in 2013 was a good predictor of survival. In 2013, we observed a 37.2% increase in hazard for every 1% increase in open grassland within the 50% MCP home range of bull elk (Figure 3.4).

Discussion

Elk in this study included a larger percentage of open land within their core area and home range than was available within the study area as a whole. The percent of open land contained in the 50% MCP core range of bull elk also influenced survival during one year of this study (2013, P=0.036; Figure 3.4), but was a poor predictor of survival in other years and at the home range scale. Additionally, I saw a marked decrease in open land inclusion in both the core and home range of adult bull elk in this study as the research progressed from 2011 to 2013. As hypothesized, mean open land inclusion in the core range was reduced by approximately 50% between 2011 and 2013.

The elk in this study overwhelmingly included a greater amount of open habitats into their daytime 50% MCP core and 90% MCP home range than is proportionally available across the study area. During a resource use analysis discussed in Chapter 2 of this dissertation, I observed the largest seasonal home ranges during the fall season and although adult bull elk selected for forest and grassland in an approximately 1:1 ratio during the daytime in the fall, we also observed higher selection for habitats near grassland patches in daytime, thus emphasizing the selection of edge habitat (Chapter 2: Table 2.3).

Interestingly, the percent of open land within both the fall core and home range of bull elk in this study was significantly reduced each subsequent year of the study (2011-2013). Open land within the 50% MCP core was reduced by approximately 50% from 2011 to 2013 (Figure 3.2). The study was conducted during a period of change in Kentucky elk management in response to perceived overhunting that is thought to have peaked in 2012 (Slabach et al. 2018). The overexploitation of elk leading up to and during this study typically occurred on areas where public land was clustered (Slabach et al. 2018). Elk management in Kentucky transitioned from a zone system to a limited entry area (LEA) system between the 2012 and 2013 hunting seasons in an attempt to limit localized overharvest on and around these public land clusters (KDFWR 2015, Slabach et al. 2018), including the public lands within the study area. During this transition, hunter numbers in the study area were reduced from 115 (2011-2012) to 65 (2013). The authors postulate that the increased level of hunting pressure in 2011-12 may have led to elk spending less time in open habitats within their daytime core and home range to avoid disturbance and the potential of hunter harvest.

The tradeoff between forage habitat versus escape habitat and the benefits of edge habitat have been studied and identified for ungulates (Kie et al. 2002, Walter et al. 2009). Generally, the assumption is that species use edge habitat to limit their predation chances while being in close proximity to the preferred nutritional elements found in open habitats (Masse and Cote 2012). In our study area, mining activity has produced grassland gaps of varying size within a predominately forested landscape. The canopy gaps have in turn, contributed to an increased level of habitat heterogeneity (Masse and Cote 2012). With an understanding that elk and other large herbivores demand some level of habitat

heterogeneity (Kie et al. 2002), the human-mediated landscape disturbance present in the study area may increase the overall landscape suitability for elk in this region (Larkin et al. 2004).

During the fall season (September 1 to October 15), elk in the study area were subjected to an increased level of disturbance through recreation from hunters, all-terrain vehicles (ATV) use and horseback riding. Over 160 km of ATV and horseback riding trails were located on a 17,400ha tract of public land within the study area. Wisdom et al. (2018) observed elk avoiding trail areas during times of use in a controlled experiment using ATV, horseback riding, hiking and biking as the disturbance factors. ATV use resulted in elk moving the greatest mean distance from the trail and caused elk to display the same level of avoidance as found from vehicle use on roadways (Wisdom et al. 2018). Unique to the Kentucky elk restoration zone is that most trails and human disturbance are centered on open, reclaimed mine areas where mining practices have produced grassland areas primarily on the ridgetops (Maigret et al. 2019). From a hunting standpoint, elk are more available to hunters in open areas (Ciuti et al. 2012, Thurfjell et al. 2017) and thus hunters likely focus their efforts on surveying open areas as opposed to hunting the more difficult to access timbered habitats. Additionally, mining practices greatly improve access to grassland and forested ridgetop habitats (Maigret et al. 2019), allowing hunters improved access to these areas. The above-listed factors may have contributed to the reduction in the percent of open land included within the daytime, fall core area and home range of bull elk in this study over the course of three fall hunting seasons.

Elk fleeing to security cover has been observed in many western elk herds when faced with hunting pressure (Millspaugh et al. 2000, Proffitt et al. 2010, Proffitt et al. 2013,

Ranglack et al. 2017) or other forms of recreational disturbance (Wisdom et al. 2018). It has additionally been observed that elk will seek lands with limited or no hunting pressure. Hunting disturbance of a Montana elk herd revealed that female elk select for land with less hunting pressure as opposed to prioritizing security cover (Proffitt et al. 2013). This finding is in parallel with many studies that show elk selecting for areas with less hunter harvest risk (Burcham et al. 1999, Vieira et al. 2003, Proffitt et al. 2009, Proffitt et al. 2010). Within Kentucky, it has been established that female elk experience higher mortality rates on public land (Slabach et al. 2018), leading one to assume that some level of learned behavior would cause elk to seek areas with a lower level of hunting pressure (Thurfjell et al. 2017).

I chose to use MCP measurement of the core and home range areas of these elk due to their established history of use (Harris et al. 1990, Laver and Kelly 2008), comparability across studies, and replicability (Laver and Kelly 2008). Additionally, MCP estimates are more robust when relocation numbers are small (Harris et al. 1990), which allowed me to include elk harvested early in the seasonal period that included fewer relocations. As per the MCP sizes chosen, because most mammalian species use their home range unevenly during the course of a seasonal time frame (Harris et al. 1990), I chose to investigate a 90% MCP as the home range and a 50% MCP to represent a core area of use. In keeping with Harris et al. (1990), I made the assumption that the daytime core area (50% MCP) for male elk will be areas of security cover used to bed with their harem. With movement likely restricted during the daytime of the fall season due to rutting activity and warm temperatures, MCPs represent a home range measurement technique that is somewhat resilient to the impacts of autocorrelation (Harris et al. 1990, Rooney et al. 1998). The

collection of location data at 0900, 1300 and 1700 represent distinct time periods where male elk are likely to be in different activity modes thus further temporally unlinking the data (Robertson et al. 1998, Rooney et al. 1998, Katajisto and Moilanen 2006). With the understanding that the use of MCP as a home range metric assumes an equal probability of use across the area circumscribed by the representative polygon (Katajisto and Moilanen 2006), the authors chose this metric to include habitats within proximity to the animal but not heavily used. For example, large grassland areas situated in proximity to forest cover could facilitate observation of and access to elk residing within forest cover. The more conservative delineation of home range areas by kernel methods (Harris et al. 1990, Katajisto and Moilanen 2006) may exclude important habitat features identified by using MCP.

When pooled across all three years of this study, the percent of open land within the core area and home range of bull elk was a poor predictor of survival. Pooling across years was necessary to accomodate a small sample size/year and was likely impacted by the variation in the percent of open land across each year of the study (Figure 3.2). Indeed, our results may be skewed by a low sample size as well as a low number of mortality events in 2011 and 2013, when compared to those of 2012. Additionally, very few elk contributed location and survival data for more than one season, with only twelve elk contributing location data to two seasons and zero elk contributing to all three seasons. I observed 26 mortality events during the course of this study, yet the majority (16) of these events occurred in 2012 (Table 3.2).

A regulatory shift from a zone system to a LEA system, prescribed prior to the 2013 hunting season, may have led to increased survival odds when compared to the low survival

rates observed in 2012. The animals discussed here were part of a larger study described in Chapter 1 and in Slabach et al. (2018), where additional animals wearing very high frequency (VHF) collars bolstered the sample size while reducing the price per data point compared to using all GPS equipment. A larger sample of GPS equipped animals would likely provide more precise estimates of the amount of open land and improve the confidence intervals of all survival analyses. In light of these possible shortcomings, my results indicated a significant inverse relationship between the percent of open land within a 50% MCP core area of bull elk and survival during the fall of 2013. Future work should include a larger sample of GPS collared elk across multiple years to account for the wide variances in survival that can be caused by management changes and stochastic events (e.g. disease outbreak). Additionally, other habitat variables and most importantly, measured disturbance, should be more carefully quantified so as to be included in future models to more clearly define the impacts of hunting and trail recreation on elk habitat use in this region.

Management Implications

Elk managers in the east should consider the interaction between open access lands, recreation intensity, and available habitat, particularly grasslands, when developing elk hunting regulations. Given the potential of open land to influence survival, such as were observed in the fall of 2013, areas with a high percentage of open land should be carefully monitored to reduce the potential for localized overharvest.

Acknowledgments

The authors would like to thank the various guides and hunters who assisted with sample collection and made us aware of hunter-harvested animals. We thank B. Owens, R. Ownes, C. Haymes and J. McDermott for their assistance monitoring and recovering bull elk during the fall hunting seasons. This research was funded by grants from the federal McIntire-Stennis program, Pitman-Robertson (PR) funds administered by the Kentucky Department of Fish and Wildlife resources, as well as by a Project Acquisition Committee grant through the Rocky Mountain Elk Foundation. We also thank C. Osborne and the staff at the University of Kentucky's Robinson Forest for housing and assistance during our field stay.

Table 3.1. Percent habitat cover type found within fall season 50% core and 90% home range minimum convex polygons for elk in eastern Kentucky. Data were pooled across 2011-2013.

	Bare Ground	Grass	Timber	Open Land
Study Area	2.4	6.8	90.8	9.2
50% MCP	6.7(13.6)	38.3(28.9)	54.9(33.0)	45.1 (32.9)
90% MCP	6.5(10.3)	33.9 (23.4)	59.4(25.7)	40.6 (26.7)

Table 3.2. Survival probability of GPS marked bull elk in the Kentucky elk restoration zone as indicated by a Kaplan-Meier analysis from 2011-2013. Odds of survival are presented as a percentage with upper and lower 95% confidence intervals.

Year	n	Odds of Survival	Lower CI	Upper CI
2011	17	76.5	58.7	99.5
2012*	21	23.8	11.1	51.2
2013	19	68.4	50.4	92.9

* Indicates significant log-rank test

Figure 3.1. Map of the 16-county Kentucky elk restoration zone used to investigate habitat use and mortality of bull elk from 2011 to 2013. Our study covers 87,570 ha within the bold, black square. Fall season, daytime locations of all three fall hunting seasons (2011, 2012 and 2013) are plotted within the study area.

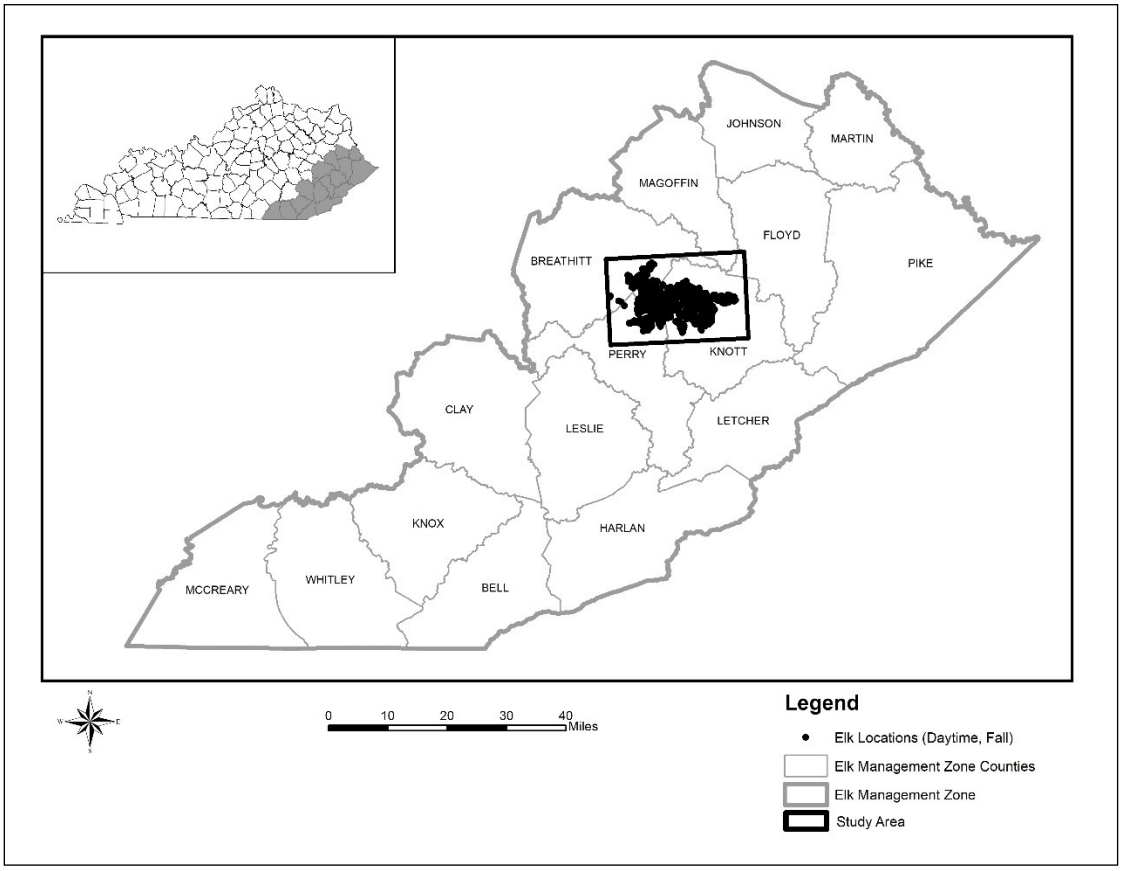


Figure 3.2. Mean percent open land in the 50% MCP core area and 90% MCP home range of bull elk in each fall hunting season (2011-2013), within the Kentucky elk restoration zone. Means are presented as a black dot inside of standard deviation error bars. Tukey's test was significant between all combinations except for the 50% MCP between 2012 and 2013.

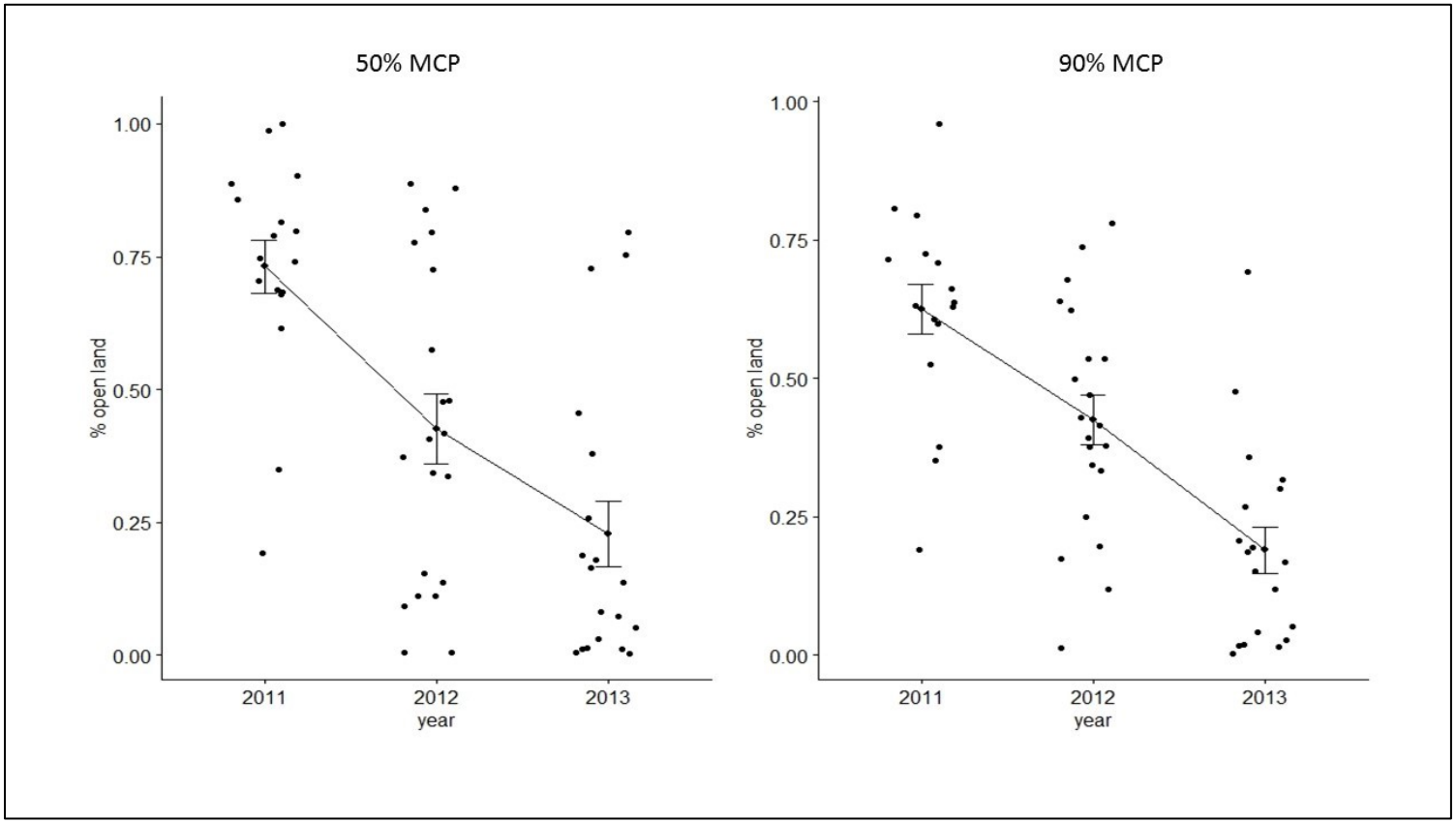


Figure 3.3. Kaplan-Meier curves for Kentucky bull elk that contributed GPS location data to this study stratified by year (2011, 2012 and 2013) and plotted against time in days. Survival estimates for 2012 were significantly different from that of 2011 and 2013 as indicated by a log-rank test at an alpha level of 0.05.

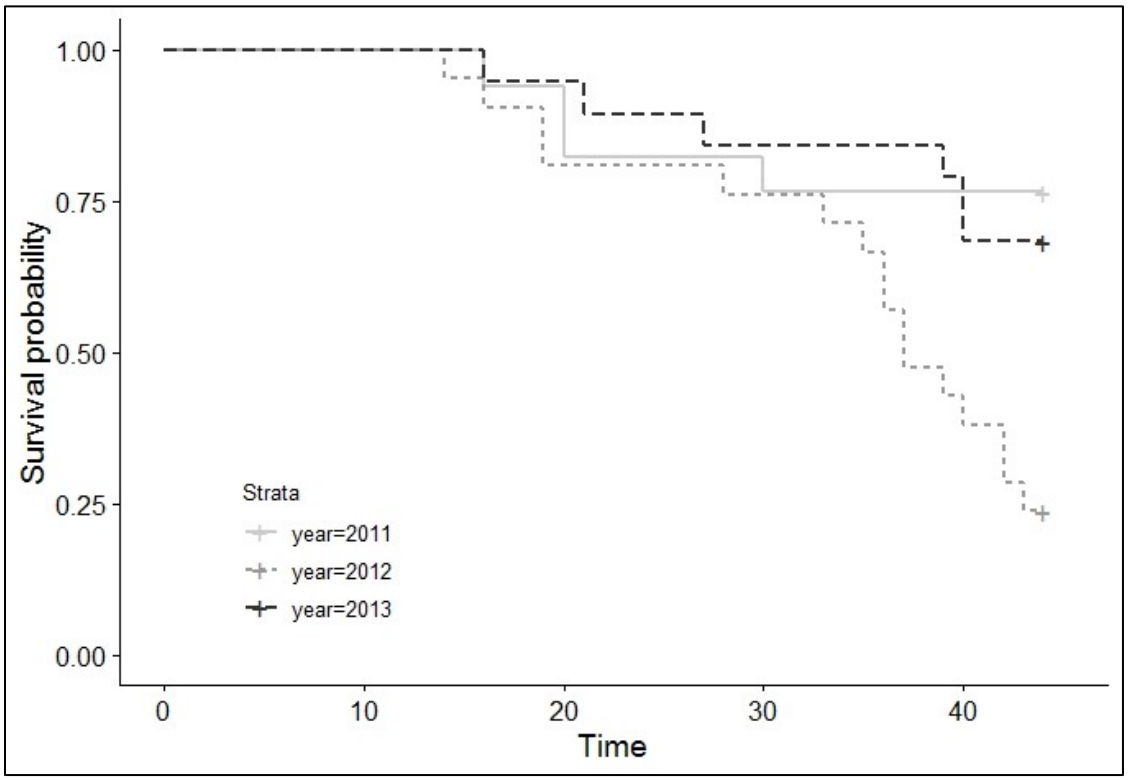
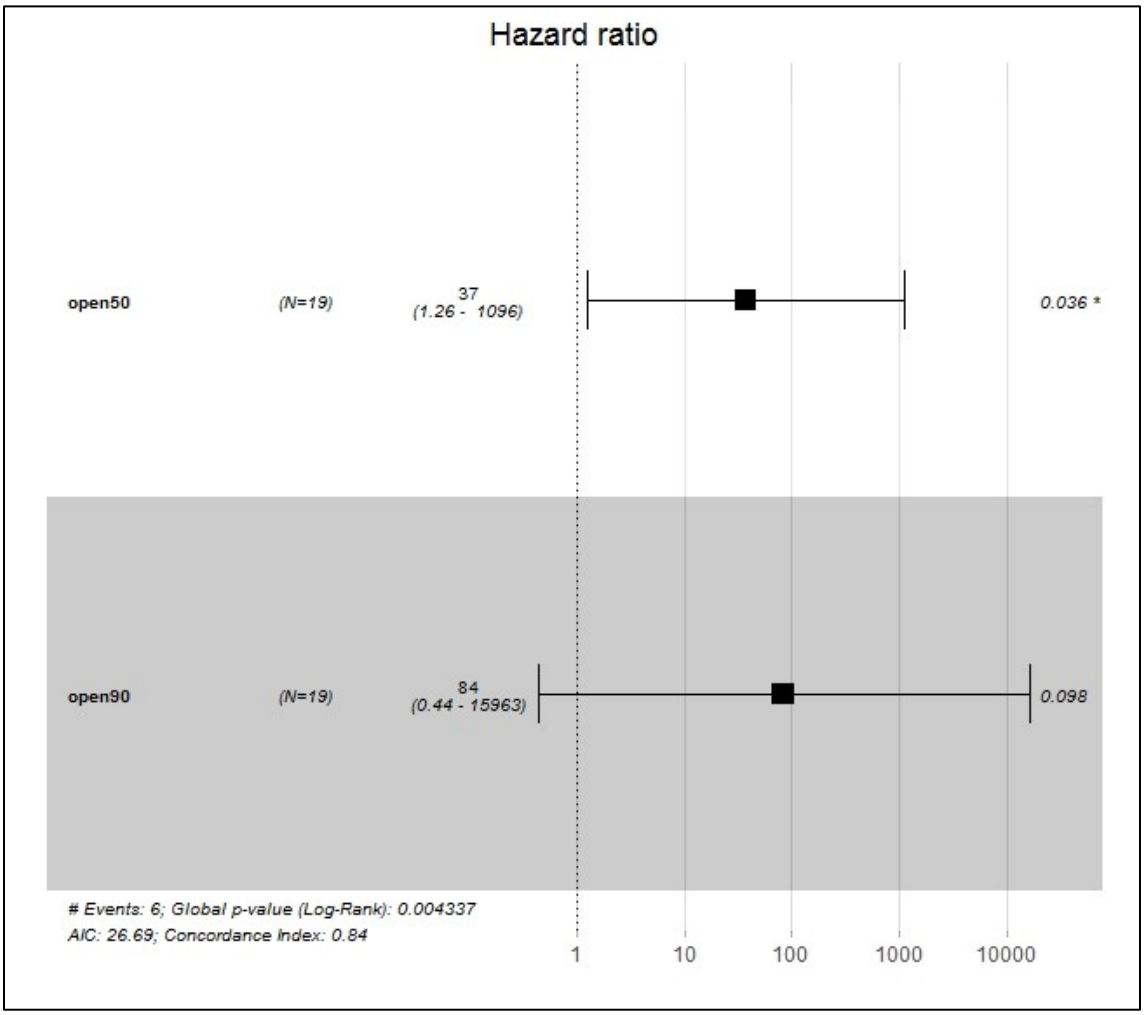


Figure 3.4. A forest plot of the influence that percent open land within a 50% MCP core area and 90% MCP home ranage has on bull elk survival within the Kentucky elk restoration zone in 2013. In 2013, adult, male elk were subjected to a 37.2% increase in hazard for every one percent increase in open land within their 50% MCP core area.



CHAPTER 4. FIELD IMMOBILIZATION OF ELK WITH CARFENTANIL CITRATE

Abstract

In an effort to inform field immobilization techniques and elk capture in general, I recorded a number of capture and reversal metrics using Carfentanil citrate at a dose of 2.7 or 3mg and naltrexone at a dose of 100mg per 1mg of Carfentanil delivered. I recorded drug induction metrics that included time at first sign, sternal or lateral recumbancy, head down and run distance. Reversal metrics included first sign of reversal, head up, sternal, standing and full recovery.

Two hundred and thirty-nine adult elk were captured from 2011-2014. All induction metrics, aside from time to first sign could be pooled across dose and sex groups. Run distance after dart impact averaged to 110.5m (SE = 5.5) across sex and dose groups. Linear regression models applied to the induction metrics indicated that the variables of dose group, injection site and temperature were capable of predicating the induction metrics. The influence of injection site was significant when considering time to head down with a hindquarter injection taking 0.7 min longer than a shoulder injection ($p = 0.815$). The average length of the dart shots was 54.1m (SE = 0.9) and shot distance predicted a good or poor injection site with the probability of a poor shot increasing by three percent for every one meter increase in darting distance. For the reversal metrics, time to full recovery for the pooled group averaged to 5.1 min (SE = 0.1) while taking slightly longer for the male group.

Introduction

Safe capture and handling of wildlife minimizes the risk of injury and death to animals and humans, and has become a codified ethical practice of institutions globally (Bush 1992, Kreeger and Arnemo 2012). Large mammals are particularly challenging to capture and safely process for management and research purposes because their size poses an increased risk of self-injury or harm to animal handlers when stressed or drugged (Miller et al. 1996, Kreeger et al. 2010). Consequently, the development, testing, and use of immobilization drugs that safely and efficaciously tranquilize large mammals has been paramount in advancing research in such fields as veterinary science, wildlife biology and management (Bailey et al. 1985, Bush 1992, Kreeger et al. 2010).

Opioid drugs, including Carfentanil, are often preferred for the immobilization of many large mammals due to low drug volumes, rapid induction times and full reversibility (Meuleman et al. 1984, Miller et al. 1996, Kreeger et al. 2011, Kreeger and Arnemo 2012); characteristics that are of heightened importance when using remote drug delivery devices on free-ranging animals in remote, difficult habitat conditions. Carfentanil is the most potent of the morphine derivatives (Wax et al. 2003, George et al. 2010, Stanley 2014, Cole and Nelson 2017) and has been evaluated in white-tailed deer (*Odocoileus virginianus*) (Miller et al. 2003, Storms et al. 2005), Pacific walruses (*Odbenus rosmerus divergens*) (Mulcahy et al. 2003), moose (*Alces alces*) (Meuleman et al. 1984), black bears (*Ursus americanus*) (Ramsay et al. 1995, Kreeger et al. 2013), grizzly bears (*Ursus arctos*) (Kreeger et al. 2013), various non-human primates (Kearns et al. 1999), African elephants (*Loxodonta africana*) (Jacobson et al. 1988) and common eland (*Taurotagus oryx*) (Cole et al. 2006), among others. Carfentanil has been used to immobilize elk (*Cervus*

canadensis) both with and without the synergistic properties of an alpha$_2$ agonist, such as xylazine (Stanley et al. 1988, Haigh 1990, Haigh 1991, Kreeger and Arnemo 2012, Kreeger et al. 2013).

Animal immobilization using a remote device (e.g. rifle-propelled dart) under field conditions presents a variety of challenges that can lead to inconsistencies in drug delivery (variability in injection site location and drug volume delivered). Understandably, these challenges make it difficult for optimizing drug parameters and testing drug efficacy under uncontrolled field conditions (Haigh 1990, Bush 1992, Miller et al. 1996). Nonetheless, evaluation of drugs for animal immobilization in a variety of field conditions can provide valuable insight into general or single-species applications. These "real world" tests can inform animal handlers about general drug efficacy, their physiological and behavioral effects on animals, and challenges posed in their use, particularly where robust sample sizes of a single species under similar field conditions are used within a single study.

Most studies evaluating the efficacy of Carfentanil have been carried out in controlled environments with drug delivery occurring via intramuscular (IM) injection by hand (Meuleman et al. 1984, Haigh 1991, Cole et al. 2006). Studies that employed remote drug delivery of Carfentanil identified a lack of drug efficacy when an IM injection was not achieved (Haigh 1991). Additionally, an increase in the time to recumbancy was noted when using remote delivery as opposed to a more controllable hand IM injection (Meuleman et al. 1984, Haigh 1990, Haigh 1991).

We opportunistically examined the general efficacy and safety of Carfentanil in immobilizing elk captured during a multi-year, radio-telemetry study in southeastern

Kentucky. We hypothesized that: (1) drug induction metrics would vary by sex and dose group, (2) sex, injection site and dose would be significant predictors of drug induction metrics, (3) Naltrexone antagonist metrics would vary by dose group but not by sex, (4) a frontal injection site, as opposed to a hindquarter injection site, would reduce the time to head down and run distance induction metrics, and (5) darting distance would increase during the project with longer shot distances resulting in less favorable injection sites.

Methods

We captured elk within 3 study areas of the 16,802 km^2 Kentucky elk restoration zone in the southeastern corner of the state (Figure 4.1), a region characterized by steep hills of 300-1300m in elevation, deep dendritic drainages, and narrow valleys (Larkin et al. 2001). Adult elk of both sexes were immobilized using free-range darting from 1 January 2011 to 26 March 2014. Elk were darted using a 1ml, wire barbed, rifle propelled dart (Pneu-dart, Williamsport, PA) filled with a solution containing 2.7 or 3 mg of the immobilization drug Carfentanil citrate (Zoopharm, Windsor, Colorado, USA; concentration = 3 mg/ml) per the suggested dosage of 0.01-0.02 mg/kg of estimated body weight (Kreeger and Arnemo 2012). Researchers attempted to target large muscle groups (e.g. hind quarters or shoulder) with darts, and injection site was subsequently recorded to investigate differences in drug induction metrics caused by injection site location. The distance between the shooter and the elk at the point of dart impact was either visually estimated or determined using a laser rangefinder when available. Darted elk were observed when possible, and researchers recorded flight distance from the site of impact, time at first sign of induction, time at sternal or lateral recumbancy, and time at head down. Flight (run) distance, the distance in meters that an elk moved between the dart impact and

full immobilization, was estimated or calculated using a laser rangefinder or a GPS unit. Fully immobilized elk were quickly approached and placed in sternal recumbancy to reduce the potential for bloating and aspiration. Ophthalmic ointment was immediately applied to the eyes to reduce corneal damage, and a blindfold was used to reduce visual stressors. Physiological responses to the immobilization event, such as rectal temperature, respiration and pulse rate were collected opportunistically while the elk was immobilized. Additionally, ambient air temperature was collected using the digital thermometer in our field vehicles as a proxy for the drug temperature at the time of injection. Most adult elk were fitted with radio tracking collars and individually numbered ear tags.

Immobilized elk were recovered via a shoulder or hindquarter IM injection (reversal injection location not recorded) of the antagonist Naltrexone hydrochloride at a rate of 100 mg per 1 mg of Carfentanil delivered (Miller et al. 1996) except that those elk receiving a 2.7 mg dosage of Carfentanil received Naltrexone sufficient to reverse a 3 mg dosage. Researchers observed recovering elk from a safe distance (~50-100m) and recorded time at first sign of recovery (first post-reversal movement made by the animal), time at head up, time at sternal recumbancy, time at standing, and time at full recovery. Time at full recovery was defined as this time when the previously immobilized elk fled or moved from the immediate area where the workup was performed. We considered elk to be fully recovered when they were ambulatory and exhibited no visible signs of disorientation or imbalance. Elk capture and immobilization procedures were approved under University of Kentucky IACUC protocol # 2010-0726.

We recorded drug induction metrics of first sign, sternal or lateral, head down and run distance. Sample sizes varied for each analysis due to metrics being unavailable for

some elk, in most cases where we attempted to observe the animal following remote drug delivery but lost immediate sight of it before it became immobilized. Subsequently, any elk missing an induction metric was removed from that particular analysis. To remove as much stochastic variation as possible, we chose not to include elk that required a second remote delivery of Carfentanil to reach sternal or lateral recumbancy.

The effects of the drug antagonist Naltrexone were tested using the following recovery states: first sign of reversal, head up, sternal position, standing and full recovery. Normality of data was tested using a qqplot from the car package (Fox and Weisberg 2019) within the R statistics program (Team 2012). For each induction and reversal metric, outliers were removed from the pooled induction metrics to remove extreme values using a boxplot in the base statistics package of the R program. To determine if it was possible to pool data across sex and dose groups, an analysis of variance (ANOVA) was performed in R on four dosage groups: male 1.0 (3 mg), male 0.9 (2.7 mg), female 1.0 (3 mg) and female 0.9 (2.7 mg) and by sex for the reversal metrics. Post-hoc analysis of possible differences between dosage groups was conducted using a Tukey's test. Normality was again tested at this point with a normality plot of the residuals. If pooling was possible, we presented pooled data along with an analysis by dose group. To visualize the results, boxplots were built using the ggboxplot function within the ggpubr package (Kassambara 2019) in R. The aggregate function was used to calculate mean and standard error by dose group and or sex, while the mean function from the base package and std.error function from the plotrix package (Lemon 2006) were used to calculate summary statistics for the pooled cohorts.

Predictive models were calculated for the induction metrics using linear regression in R. A data frame was prepared for each induction metric using only animals for which the time points were observed. Again, outlying data points were removed via boxplot. The full model for the linear regression analysis is described below:

Model 1: Y ~ sex + dose + (sex*dose) + injection site + darting distance + temperature

For this analysis, injection site was divided into two categories, a belly or muscle hit, representing a poor or suitable intramuscular injection, respectively. Model selection was accomplished using stepwise selection as well as through the removal of non-significant (alpha level > 0.05) predictive variables from the suggested model. Multicollinearity was investigated by calculating variance inflation factors (VIF) for all variables in the final model using the VIF function within the car package (Fox and Weisberg 2019) in R.

We examined the effect of injection site on flight distance and induction metrics. For this analysis, we considered both shoulder shots, and those shots at the very base of the neck, as a shoulder injection site. A qqplot in the car package (Fox and Weisberg 2019) was used to test for normality of our two variables, time to head down and run distance. Outliers within these two variables were removed via boxplot. An ANOVA coupled with a Tukey's test was used to determine if pooling was applicable between sexes and dosages. An ANOVA was additionally used to evaluate the difference between injection sites when considering time to head down and run distance. Summary statistics were calculated using the aggregate function.

The influence of injection site was additionally evaluated using linear regression to develop a predictive model for time to head down and run distance at an alpha level of 0.1. The models evaluated for time to head down and run distance are described below:

Model 2: Time to head down ~ injection site + sex + dose + (sex*dose)

Model 3: Run distance ~ injection site + sex + dose + (sex*dose)

Multicollinearity was investigated by calculating variance inflation factors (VIF) for all variables in the final model using the VIF function within the car package (Fox and Weisberg 2019) in R.

To investigate the interaction of darting distance and shot placement, normality was checked with a qqplot (Fox and Weisberg 2019) and outliers in the shot distance measurement were removed using a boxplot. Summary statistics by year were calculated using the aggregate function. The mean function from the base package and std.error function from package plotrix (Lemon 2006) were used to calculate summary statistics for all dart shots pooled across years. Results were illustrated using a ggline plot from the ggpubr package (Kassambara 2019). To evaluate the interaction between shot distance and the quality of the injection site, we used the glm function to perform a logistic regression on the following model:

Model 5: IM injection ~ dart distance + sex + dose + (sex*dose)

Those injection sites that will likely deliver an IM injection were classified as “good” while areas such as the belly, ribs and lower extremities were classified as “poor” injection sites.

Results

We darted 239 adult elk (185 M, 54 F) from 2011-2014 and recorded induction and reversal metrics. A Tukey's test applied to each drug induction metric indicated that time to sternal or lateral, time to head down and run distance could be pooled across dose groups. The Tukey's test found significant differences between the dose groups of male 1.0 and female 0.9 ($p=0.011$; Table 4.1) that preclude a pooled analysis for the time to first sign metric. Time to first sign occurred most quickly for the male 1.0 dose group (mean = 2.6 min, SE = 0.2), followed by the female 1.0 dose group (mean = 2.7 min, SE = 0.3), the male 0.9 dose group (mean = 3.0 min, SE = 0.3) and finally the female 0.9 dose group (mean = 3.9 min, SE = 0.3; Table 4.1; Figure 4.2). For the pooled analysis, time to sternal or lateral recumbancy could be expected in 4.2 min (SE = 0.1), while time to head down averaged 4.6 min (SE = 0.1). Run distance after the dart impact averaged to 110.5m (SE = 5.5) from a sample of 175 elk pooled across dose groups.

Linear regression models applied to the induction metrics indicated that the variables of dose, injection site and temperature were capable of predicting the induction metrics (Table 4.2). Time to first sign was reduced by using a 3mg dose and delivering the drug intramuscularly. Time to sternal or lateral shortened as temperature declined and by delivering an intramuscular injection. Time to head down, evaluated at an alpha level of 0.1, was reduced as temperature declined ($p = 0.06$). Run distance was reduced by delivering an intramuscular injection (Table 4.2). VIFs for all variables in the final model were < 2.

A Tukey's test applied to the reversal metrics by dose group indicated no significant difference between dose groups. As such, we chose to present pooled results along with

results by sex (Table 4.3). Time to first sign could be expected at 2.5 min (SE = 0.1) for the pooled cohort. Time to head up occurred on average at 3.3 min (SE = 0.1) for the pooled, male and female cohorts. Time at sternal and at standing could be expected at 3.9 min (SE = 0.1) and 4.5 min (SE = 0.1), respectively. Time to full recovery took slightly longer for the male cohort versus the female cohort, while the pooled group averaged 5.1 min (SE = 0.1; Table 4.3)

ANOVA results, coupled with a Tukey's test, indicated that we could pool animals across dose groups to investigate the influence of injection site on the induction metric time to head down. Alternatively, ANOVA and Tukey's test results indicated a significant difference in the female 0.9 dose group from all other dose groups when considering the influence of injection site on run distance. Due to the ANOVA results, as well as a low sample size (n = 4), we chose to remove the female 0.9 dose group from the injection site versus run distance analysis, while pooling the remaining dose groups. When considering time to head down, there was a significant difference in injection site location ($p = 0.072$) when evaluated at an alpha level of 0.1 (Table 4.4). Time to head down for a hindquarter shot could be expected at 5.1 min (SE = 0.3) while a shoulder shot could be expected at 4.4 min (SE = 0.2). Injection site versus run distance did not produce a significant ANOVA result ($p = 0.815$), indicating no advantage in injection site on the reduction in run distance (Table 4.4; Figure 4.3)

When considering the influence of injection site on run distance, no variable significantly contributed to a predictive model. Alternatively, time to head down was reduced by 0.6 min when using a shoulder injection as described in the following model:

Model 5: Y ~ 5.1 + (-0.6 * injection site shoulder)

All VIFs in the final model were less than 2. Average darting distances lengthened between 2011 and 2013 and then reduced slightly during the final year of the project (Table 4.5; Figure 4.4). A Tukey's test indicated significant differences ($p = 0.038$) between the mean darting distance of 2011 (mean = 47.7m, SE = 1.7) and 2013 (mean = 59.0m, SE = 1.3). When pooling all years of the study ($n = 239$), the average length of a dart shot was 54.1m (SE = 0.9), with a range of 18 to 87m. Darting distance was a significant predictor of a "good" or "poor" injection site ($p = 0.027$), with the probability of a "poor" dart hit increasing by three percent for every one meter increase in darting distance ($n = 206$, OR = 0.97).

Discussion

We retrospectively analyzed the induction and reversal metrics for elk remotely delivered two standard doses of Carfentanil, antagonized with a standard dose of Naltrexone under field conditions. This project was not designed to establish specific drug dosage parameters, but instead to characterize the general efficacy of the recommended dosage of Carfentanil using remote drug delivery under field conditions (Meuleman et al. 1984, Miller et al. 1996, Moresco et al. 2001). During fieldwork, researchers were going afield equipped to dart any elk encountered to answer a variety of ecological questions. As such, we initially chose to use a 3mg dose of Carfentanil, while later reducing that to 2.7mg. This reduction in dose allowed for an extra dose from each bottle of drug, thus allowing us to stretch a limited supply of immobilization drug while still producing desired results. The

two doses used in this project were sufficient to immobilize all age classes of elk with good results.

In assessing hypothesis one, drug induction metrics did vary by sex and dose when evaluating time to first sign, but results were consistent among sex and dose for the other induction metrics. The null hypothesis that sex, injection site and dose would be significant predictors of the induction metrics held true. We rejected the hypothesis that reversal metrics would vary by dose, concluding no differences among sex and dose groups. Our hypothesis that a frontal shot would result in a reduction in the time to head down held true yet was rejected for run distance. Finally, darting distance did increase over the first three years of the capture efforts and longer shots were slightly more likely to result in less desirable injection sites.

Of those elk still standing after the initial dose was deemed ineffective (n = 8), all were approached and delivered 0.75 mg of Carfentanil, resulting in desired immobilization results. We were unable to determine why the original dose was ineffective in all cases. Secondly, we used a standard boxplot to remove outlying points from the pooled induction and reversal metrics. These outlaying points were deemed influential and likely the result of factors that could not be quantified. The outlaying points can likely be attributed to physiological attributes of the elk, dart or projector malfunction, drug leakage or an insufficient IM injection (Haigh 1991, Bush 1992).

Even the confirmation of a hit into a "good" injection site does not guarantee an IM injection due to the potential for the drug to be deposited into fat or connective tissue in close proximity to a muscle mass (Haigh 1991, Bush 1992). Additionally, the use of a

powder-fired dart, such as those used in this study, have the potential to damage tissue (Bush 1992) and prevent the efficient uptake of the immobilization drug (Kreeger and Arnemo 2012). Haigh (1991), Haigh (1990) and Meuleman et al. (1984) all observed nearly twice the length of time required to achieve recumbancy when using a remote delivery device as compared to a hand IM injection. This increase in immobilization time was attributed to the dart impact and subsequent muscle disturbance and damage (Haigh 1991). Our project was conducted under field conditions, resulting in many difficulties with the acquisition of precise measurements. Researchers were unable to weigh elk in this study, a key variable that would likely have better informed our predictive models. Very seldom are pre-capture weights available to allow the drug dose to be custom tailored to that individual animal, and instead, post-capture weights are often used for analyses. Instead, we operated with two drug doses that had been evaluated for efficacy prior to this project (Meuleman et al. 1984, Miller et al. 1996, Moresco et al. 2001).

Many studies of elk immobilization with Carfentanil employed the synergistic effects of an alpha$_2$ agonist such as Xylazine (Haigh 1991). Haigh (1991) found that time to recumbancy averaged 4.9 min using a Carfentanil and Xylazine dose delivered via remote injection at 0.037 mg/kg and 0.14 mg/kg, respectively. Using a similar dose as was used in our study, Miller et al. (1996) observed a mean induction time of 3.1 min after a hand IM injection of 0.01 mg/kg with a herd of captive elk. These results were mirrored by Moresco et al. (2001) where they noted an induction time of 3.9 min using a 0.01 mg/kg dose in captive elk. Meuleman et al. (1984) observed that a greater dose resulted in a quicker time to recumbancy, yet observed a mean time of 3.8 min when elk were given 0.012 – 0.066 mg/kg of Carfentanil; a dose range similar to our study. With a mean time

to recumbancy of 4.2 min (SE = 0.1), our results are well within the observed ranges represented by prior field studies and comparable to those using captive elk in controlled situations.

The potential for darting an animal in a site that precludes an IM injection is always present when utilizing remote drug delivery (Meuleman et al. 1984, Bush 1992, Kreeger and Arnemo 2012). When comparing a belly versus a muscle injection, an injection to a major muscle mass resulted in a shorter time to first sign, time to recumbancy, and run distance. This follows the suggestion of Kreeger and Arnemo (2012), where the large muscle masses are described as the best sites to place a remote drug delivery device. Additionally, anecdotal evidence from field researchers and one research study suggests that an anterior injection site produces a more rapid induction (Berrie 1972). Our work substantiates that of Berrie (1972) in that we found that time to head down was quicker for a shoulder or neck remote injection as opposed to a hindquarter remote injection ($p = 0.072$). Researchers in this study transitioned to a preference for shoulder shots as the study progressed due to quicker immobilization times and a larger area for an IM injection that remained visible at multiple angles.

A variety of opioid antagonists have been evaluated in the literature for the reversal of Carfentanil (Allen 1989). Naltrexone Hydrochloride has become the antagonist of choice due to its long-acting nature (Miller et al. 1996). Renarcotization is a serious concern when ungulates are immobilized with Carfentanil due to ataxia that may put the animal at risk for self-harm and predation (Allen 1989, Haigh 1991, Miller et al. 1996). When testing three Carfentanil antagonists, Allen (1989) found that Naltrexone, delivered at 100 mg/1 mg of Carfentanil delivered was the only evaluated antagonist that did not

produce a renarcotization event. We did experience several renarcotization events using Naltrexone at a lower dose during early capture efforts, but these were later eliminated after switching to the dose suggested by Allen (1989).

We observed a mean time to standing of 4.5 min for the pooled cohort antagonized with 300mg of Naltrexone given fully IM. Haigh (1991) evaluated reversal using Naltrexone both intravenous (IV) and IM and noted reversal times of 5.9 and 5.7 min respectively, using a dose ranging from 0.33 to 1.33 mg/kg of body weight. Using a Naltrexone dose of either 500mg/mg Carfentanil (control group) or 100 mg/mg of Carfentanil delivered 25% IV and 75% subcutaneously, Miller et al. (1996) noted that all elk were ambulatory in less than nine minutes with most ambulatory in less than four minutes. Interestingly, a difference in dose groups was not noted between the control and experimental groups (Miller et al. 1996). Researchers in this study were in general satisfied with the predictability of the reversal procedure when using a standard dose of 300mg of Naltrexone to reverse both the 2.7mg and 3mg Carfentanil dose groups present in our study.

Management Implications

We demonstrated mean induction and reversal metrics for elk immobilized with Carfentanil and antagonized with Naltrexone using remote delivery devices under field conditions. The research suggests that elk can safely be immobilized with a 2.7mg or 3.0mg dose of Carfentanil and reversed using a 300mg dose of Naltrexone. Although we also briefly experimented with a Carfentanil and Xylazine dose, we preferred the muscle rigidity afforded when only Carfentanil was used. While still being able to move elk into sternal recumbancy on flat ground, this muscle rigidity allowed us to use the elk's legs to

support the animal in sternal recumbancy on steep slopes common across the study area. Our findings suggest this drug combination provides rapid induction and recovery for elk. We further present key induction and recovery behavioral time points so that animal handlers can anticipate how elk will likely respond to this drug combination and dosage.

Acknowledgments

We thank technicians B. Owens, C. Haymes, J. McDermott, K. Sams, R. Owens, and T. Duff for their assistance with righting elk into sternal recumbancy and their patience keeping elk in sternal recumbancy during the lengthy procedures. This research was funded by grants from the federal McIntire-Stennis program, Pitman-Robertson (PR) funds administered by the Kentucky Department of Fish and Wildlife Resources and by a Project Acquisition Committee grant through the Rocky Mountain Elk Foundation.

Table 4.1. The influence of dose group on differing induction metrics for elk immobilized with Carfentanil in southeastern Kentucky, 2011-14. Results are presented as mean and standard error and pooled were applicable. A Tukey's test indicated a significant difference between the male 1.0 and female 0.9 dose groups (p=0.011).

	First Sign (min)		Stern/Lat (min)		Head Down (min)		Run Distance (m)	
Dose Group	N	Mean (SE)	N	Mean (SE)	N	Mean (SE)	N	Mean (SE)
Male 1.0 ml	95	*2.6 (0.2)	92	4.2 (0.1)	105	4.7 (0.2)	118	112.7 (3.6)
Male 0.9 ml	13	3.0 (0.3)	17	4.1 (0.4)	15	4.1 (0.3)	21	109.9 (15.4)
Female 1.0 ml	15	2.7 (0.3)	16	4.1 (0.5)	18	4.4 (0.5)	23	100.2 (14.8)
Female 0.9 ml	13	*3.9 (0.3)	9	4.4 (0.4)	5	4.8 (1.2)	13	109.4 (22.9)
Pooled	n/a	n/a	134	4.2 (0.1)	143	4.6 (0.1)	175	110.5 (5.5)
*Tukeys: p=0.011								

Table 4.2. Predictive models for drug induction metrics constructed using linear regression for elk immobilized with Carfentanil in southeastern Kentucky, 2011-14. The alpha level column indicates which alpha level was used to justify variable inclusion in the predictive model.

Induction Metric	N	Model	Alpha Level
		Time to induction metric ~ sex + dose + (sex*dose) + inject site + dart distance+ temp	
First Sign	132	Y = 4.16 + (-0.91 * dose 3mg) + (-1.68 * inject site muscle)	0.05
Sternal/Lateral	137	Y = 5.75 + (-0.03 * temp) + (-1.39 * inject site muscle)	0.05
Head Down	150	Y = 4.92 + (-0.03 * temp)	0.1
Run Distance	191	Y = 163.35 + (-55.41 * inject site muscle)	0.05

Table 4.3. Naltrexone reversal metrics by sex and pooled dose groups for elk immobilized within the Kentucky elk restoration zone. Results are presented as mean and standard error.

	Male		Female		Pooled	
Time to:	N	Mean (SE)	N	Mean (SE)	N	Mean (SE)
First Sign	137	2.6 (0.1)	44	2.4 (0.1)	181	2.5 (0.1)
Head Up	135	3.3 (0.1)	40	3.3 (0.1)	175	3.3 (0.1)
Sternal	140	3.8 (0.1)	46	3.9 (0.2)	186	3.9 (0.1)
Standing	143	4.4 (0.1)	47	4.7 (0.2)	190	4.5 (0.1)
Full Recovery	139	5.1 (0.1)	46	5.0 (0.2)	185	5.1 (0.1)

Table 4.4. Evaluation of injection site on time to head down and run distance for elk immobilized with Carfentanil in southeastern Kentucky, 2011-14. ANOVA results indicated a significant advantage to a shoulder injection site when considering time to head down.

	Time to Head Down (min)		Run Distance (m)	
Injection Site	N	Mean (SE)	N	Mean (SE)
Hindquarter	38	5.1 (0.3)	39	100.3 (9.7)
Shoulder	56	4.4 (0.2)	54	103.5 (8.8)
ANOVA p Value		0.072		0.815

Table 4.5. Mean distance from shooter to elk (dart distance) using the drug Carfentanil in southeastern Kentucky, 2011-14. A Tukey's test indicated significant differences in the mean darting distances between the years of 2011 and 2013.

Year	N	Dart Distance [mean(SE)]	Range
2011	64	*47.7 (1.7)	18-74
2012	67	54.5 (1.5)	20-76
2013	79	*59.0 (1.3)	20-87
2014	29	54.5 (2.7)	27-80
Pooled	239	54.1 (0.9)	18-87
*Tukey's: p = 0.038			

Figure 4.1. Study areas in southeastern Kentucky used for characterizing the chemical immobilization of elk using Carfentanil, 2011-14.

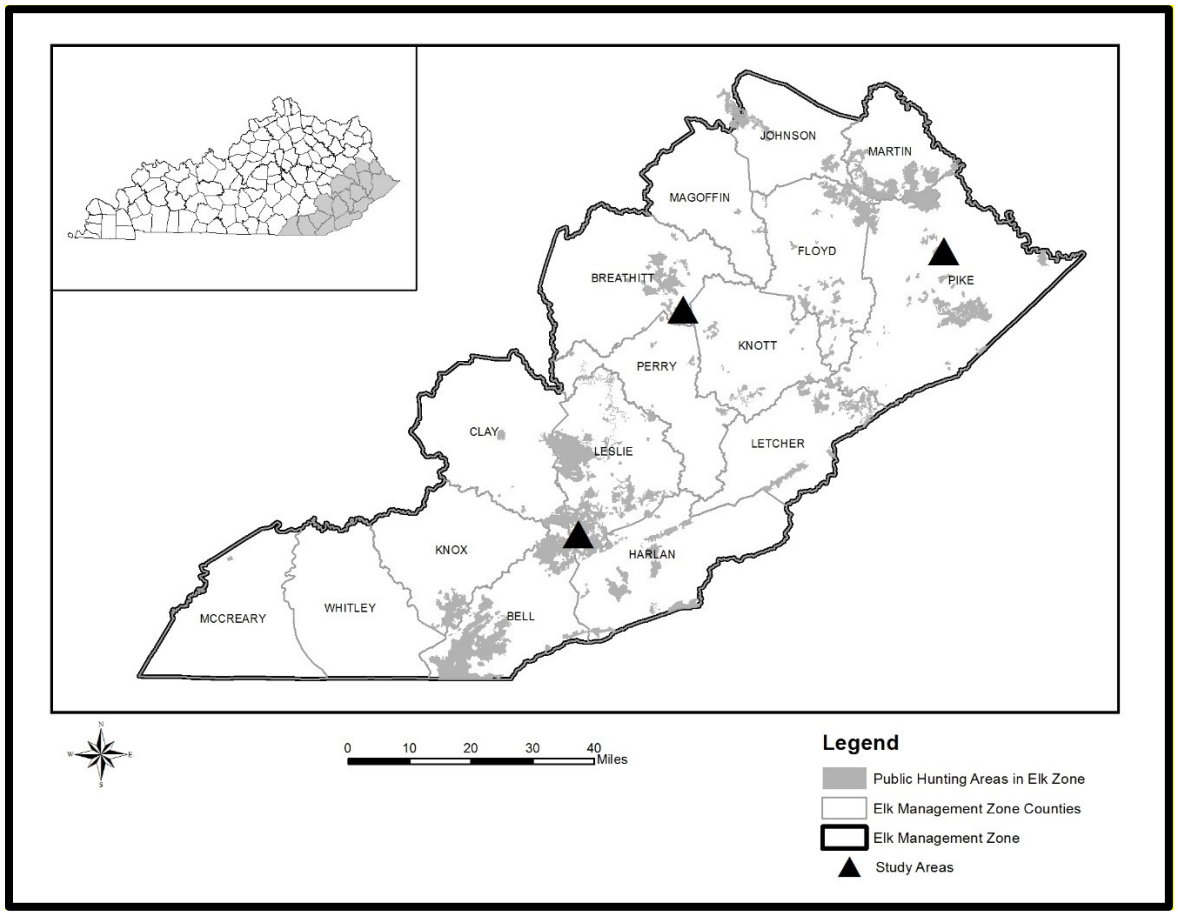


Figure 4.2. Box plots illustrating the influence of dose group on differing induction metrics for elk immobilized with Carfentanil in southeastern Kentucky, 2011-14. Outliers were removed at the onset of the analysis from the pooled values of each induction metric.

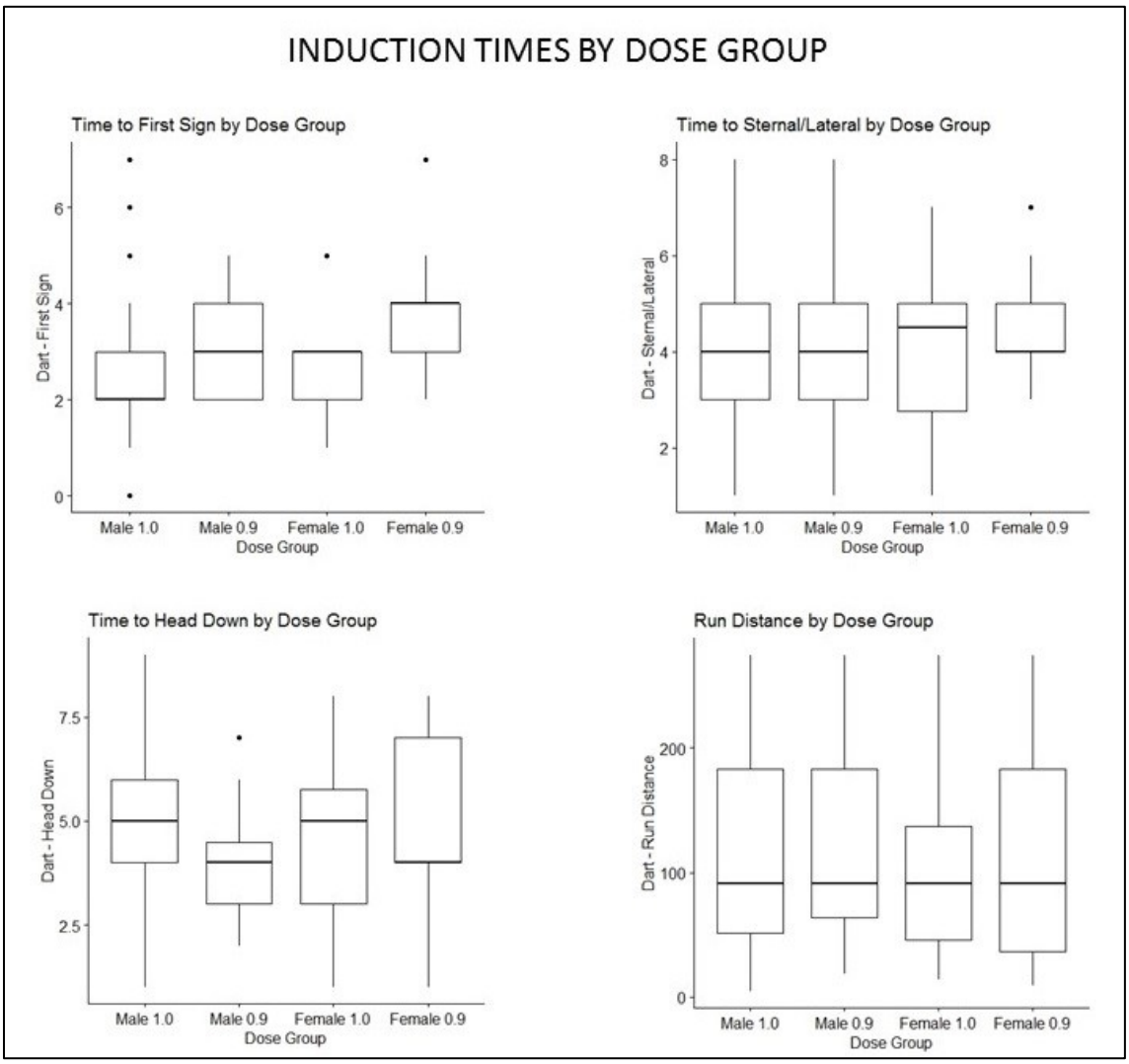


Figure 4.3. Box plot of time to head down versus injection site for elk immobilized with Carfentanil in southeastern Kentucky, 2011-14. An intramuscular drug injection in the shoulder region represents an advantage in time to head down across dose groups.

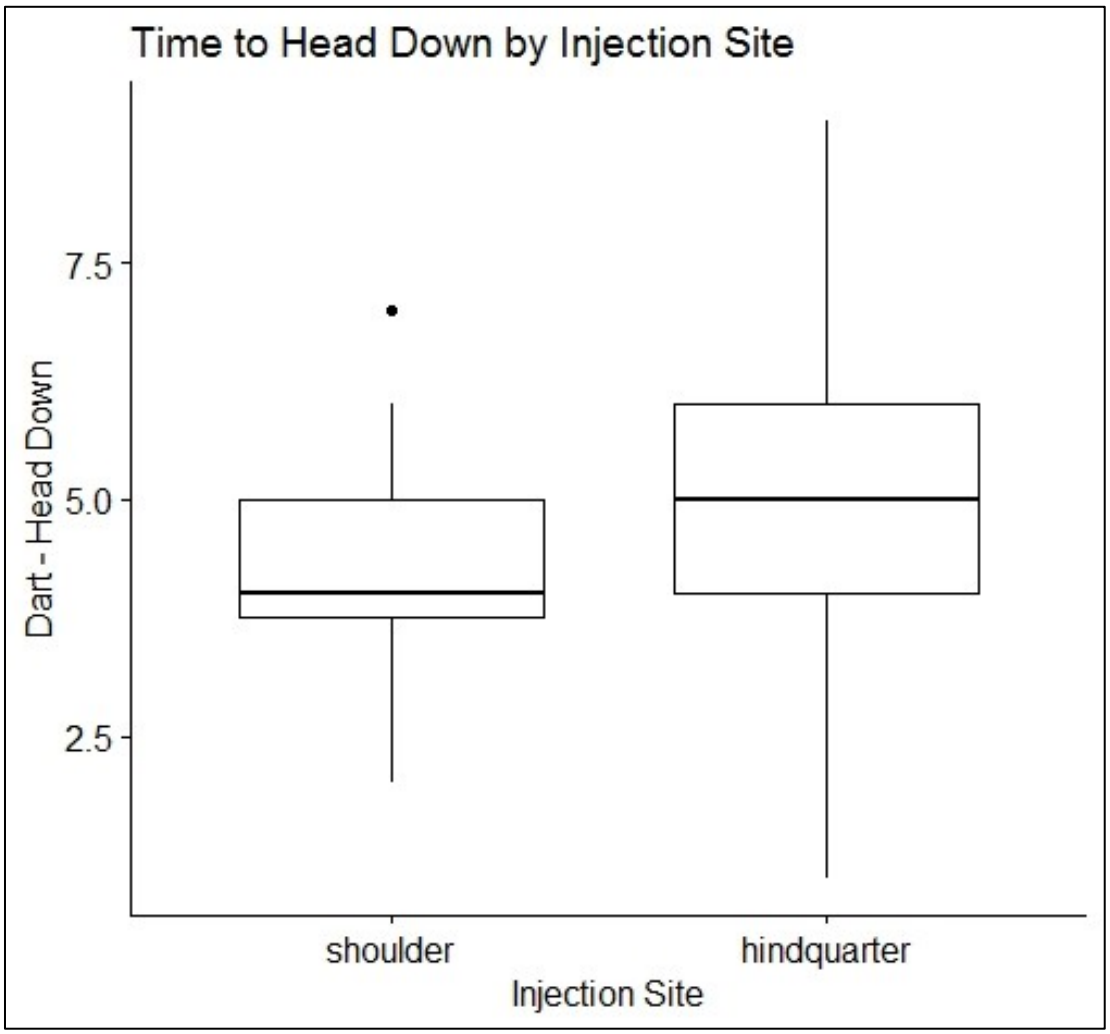
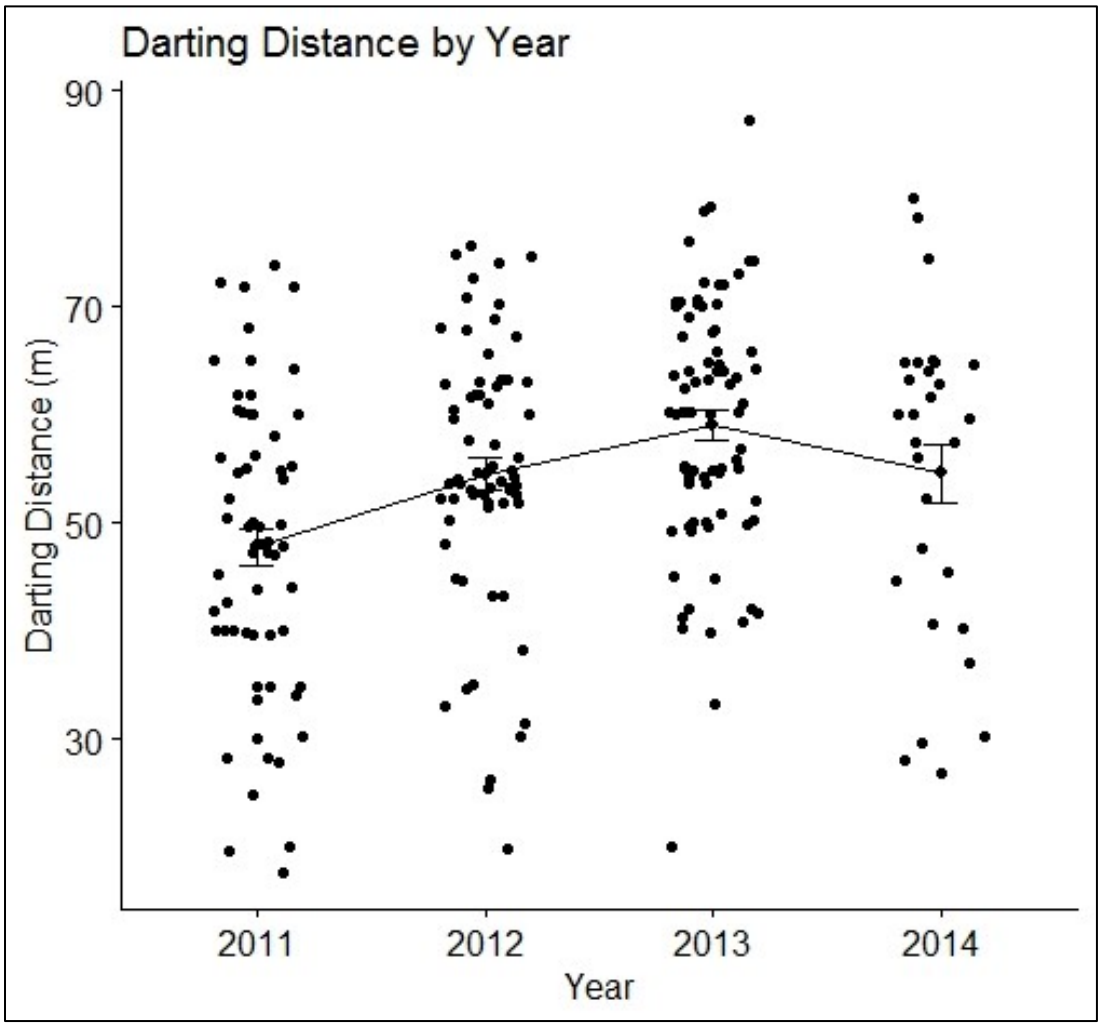


Figure 4.4. Scatterplot of distance from shooter to elk (darting distance) immobilized using Carfentanil, southeastern Kentucky, 2011-14. The mean is indicated by a black dot inside of standard error bars. A Tukey's test indicated a significant difference between the means of 2011 and 2013.



CHAPTER 5. DOES RELATEDNESS INFLUENCE SPATIAL OVERLAP IN KENTUCKY BULL ELK

Abstract

Recent publications investigating white-tailed deer dispersal and disease management have used genetic and space use methodologies to compare home range overlap and genetic relatedness. Characteristics of elk dispersal coupled with theories of breeding competition suggest that male elk should avoid sharing space with related individuals during both the rut and when forming winter and summer bachelor groups. To investigate genetic relatedness and space use overlap, I obtained microsatellite genetic data from global positioning system radio-marked adult bull elk from a study area within the Kentucky elk restoration zone. Space use overlap was quantified using volume of intersection between 95% kernel density home range estimates and linearly regressed with a measure of genetic relatedness derived from 16 microsatellite markers.

Mean relatedness and volume of intersection were largest in the winter season and smallest during the fall rutting period. When examining the linear relationship between volume of intersection and genetic relatedness, I observed a slight positive relationship in fall and summer and a negative relationship in winter, yet all seasonal linear relationships lack explanatory power. When pooled across seasons, the linear relationship was nearly flat with an R^2 value of -0.000004. I posit that the lack of dispersal influences due to the non-migratory nature of Kentucky elk does not force juvenile elk to move away from related individuals to the extent witnessed in western U.S. elk herds. Additionally, with cow herds in the study area showing strong affinity for specific locations, juvenile bull elk may only need to move a short distance to alleviate the potential for inbreeding.

Introduction

Sexual segregation occurs in many ungulate species with proximate explanations centering on anti-predation strategies and differing nutritional requirements for the male and female of the species (Main et al. 1996, Ruckstuhl and Neuhaus 2000). Male elk (*Cervus canadensis*), post-rut, typically band together in male-only aggregations while seeking security cover (Geist 2002). At this same time, male elk must replenish the nutrients lost during the rut by seeking nutrient-rich habitats that will allow for continued antler and body growth (Main et al. 1996, Geist 2002). Additionally, factors surrounding the formation of male-only "bachelor groups" implicate social drivers. More specifically for elk, the need for older males to maintain dominance outside of the fall rutting period and young males to gain and practice fighting skills necessitates male aggregations (Weckerly 2001, Geist 2002, Chapman et al. 2003). Additionally, the maintenance of antlers through the winter months allows for the efficient continuation of the dominance hierarchy established during the rutting period (Geist 2002).

Population and dispersal of polygynous ungulates is typically driven by non-dominant, young males of the species (Greenwood 1980, Petersburg et al. 2000, Smith and Anderson 2001, Killeen et al. 2014b). As is typical with other ungulates, elk disperse away from their natal home range during the second spring (Petersburg et al. 2000, Smith and Anderson 2001, Killeen et al. 2014b), with dispersal further mediated during the fall rut by the establishment of dominance hierarchies (Geist 2002). Theories on the evolutionary basis of elk dispersal include inbreeding avoidance and a reduced competition for resources and mates (Gasaway et al. 1980, Greenwood 1980, Wolff et al. 1988). Dispersal in sub-adult elk can result in increased fitness by limiting breeding competition with close

relatives (Hamilton and May 1977, Kisdi 2016), and through the discovery of nutrient resources allowing for maximum antler and body growth (Geist 2002). Not without a cost, dispersal can also put young elk at risk due to the dangers of travel in unfamiliar areas and the lack of security afforded by the natal range (Smith and Anderson 2001, Geist 2002, Killeen et al. 2014b, Mejía-Salazar et al. 2017).

This author observed male bachelor groups to be common in the winter and summer months in the study area. Typically, very few adult bulls in this population are observed with cow/calf herds outside of the rutting period, consistent with the observations of Geist (2002). One could make the assumption that these bachelor groups are same-sex congregations of post-dispersal aged male elk seeking the best nutrients to optimize their ability to establish and maintain a harem of females during future dominance contests with other males (Weckerly 2001, Geist 2002, Vander Wal et al. 2013). As such, questions arise as to the genetic relatedness of the adult male elk that occupy bachelor groups. We might expect that this maintenance of the dominance hierarchy during the winter season would preclude related elk from sharing the same space due to the evolutionary drivers behind limiting sexual competition with close relatives (Hamilton and May 1977, Kisdi 2016). During the summer season, and in the absence of hardened antlers, we would expect male elk groups to aggregate on favorable resources (Geist 2002) and exhibit a low level of dominance-based interactions (Vander Wal et al. 2013), regardless of relatedness (Vander Wal et al. 2012a). As rutting activity increases in the fall, it might be expected that summer bachelor groups would dissolve due to intra-sex competition (Geist 2002), and the sexual competition among kin theory suggests that this dissolution would in turn limit related elk from sharing the same reproductive space (Hamilton and May 1977, Kisdi 2016).

As with genetic relatedness, elk age should play a role in the space use of male elk during all seasons (Ruckstuhl and Neuhaus 2000, Weckerly 2001, Geist 2002). Young, male ungulates have an affinity for social interactions with similar aged conspecifics (Ruckstuhl and Neuhaus 2000), while developing fighting and dominance skills (Weckerly 2001). Conversely, Weckerly (2001) observed dominant Roosevelt elk (*Cervus canadensis roosevelti*) establishing enough space between other dominant elk to reduce the need for direct interaction. As such, I would expect male elk during the winter to associate with like-aged and dominance class individuals to avoid direct aggression (Weckerly 2001) and prioritize resource acquisition (Geist 2002).

Interest in dispersal and the social interaction of ungulates has been rekindled lately to investigate the transmission of important emerging diseases, including chronic wasting disease and bovine tuberculosis (Schauber et al. 2007, Vander Wal et al. 2012a, Magle et al. 2013, Mejía-Salazar et al. 2017). This interest has refined the statistical methodologies used in measuring space use overlap (Millspaugh et al. 2004), while using already established genetic techniques to measure relatedness (Magle et al. 2013, Mejía-Salazar et al. 2017). Global positioning system (GPS) and proximity sensing tracking collars (Vander Wal et al. 2012a, Vander Wal et al. 2012b) have further increased the resolution at which social interactions can be viewed (Schauber et al. 2007). Additionally, new methodologies for defining space use, using volume of intersection (VI) between utilization distributions, were developed by Seidel (1992) and evaluated by Millspaugh et al. (2004).

We used these new methods of space use estimation to investigate the impacts of genetic relatedness on space use in adult, male elk in Kentucky. Specifically, we characterized the relationship between VI, genetic relatedness (Rxy) and the age difference

between male-male elk pairs during three distinct seasons with different levels of observed elk sociality. We hypothesized that male elk in the fall season would be engaged in rutting activity with less spatial overlap than other seasons, and have an inverse relationship between VI and Rxy. With all ages of adult male elk participating in the rut, we hypothesized that the age difference between elk pairs would be a poor predictor of VI during the fall season. In the winter bachelor groups, we hypothesized that bulls would aggregate by age, thereby making the age difference of elk pairs a good predictor of VI. Additionally during winter, following the breeding competition among kin theory of Hamilton and May (1977), I hypothesized that Rxy would be a good predictor of VI. Finally, with antlers in the velvet growth stage during the summer season, I hypothesized that elk would aggregate randomly, with age difference and Rxy both being poor predictors of VI.

Study Area

The 16,802 km^2 Kentucky elk restoration zone (Figure 5.1) was comprised of 16 counties in the southeastern corner of the state bordering Tennessee, Virginia, and West Virginia. The elk zone was located within the Cumberland Plateau physiographic region that is characterized by steep hills of 300-1300m in elevation, deep dendritic drainages, and narrow valleys (Larkin et al. 2001). The dominant plant community was mixed-mesophytic forest, characterized by up to 30 co-dominant trees, including yellow poplar (*Liriodendron tulipifera*), sugar maple (*Acer saccharum*), red maple (*A. rubrum*), American beech (*Fagus grandifolia*), basswood (*Tilia* spp.), yellow buckeye (*Aesculus flava*), northern red oak (*Quercus rubra*), white oak (*Q. alba*), hemlock (*Tsuga canadensis*), black walnut (*Juglans nigra*), black cherry (*Prunus serotina*), shagbark

hickory *(Carya ovata*), and white ash (*Fraxinus americana*) (Wharton 1973). Resource extraction, predominately surface mining for coal, had altered ~20% of this region by mountain top removal and valley filling of ephemeral streams resulting in flat to rolling topography (Larkin et al. 2001). Mine reclamation in this area involves planting of native and exotic species through hydroseeding of herbaceous plants and limited hand planting of hardwoods. Common plants used in mine reclamation include Kentucky-31 tall fescue (*Lolium arundinaceum*), bush clover (*Lespedeza* spp.), birds-foot trefoil (*Lotus corniculatus*), crown vetch (*Coronilla varia*), perennial ryegrass (*Lolium perenne*), orchardgrass (*Dactylis glomerata*), black alder (*Alnus glutinosa*), autumn-olive (*Elaeagnus umbellata*), white pine (*Pinus strobus*), and black locust (*Robina pseudoacacia*) (Larkin et al. 2001). The climate in the elk zone was temperate humid continental, with warm summers and cool winters (Hill 1976). Mean annual temperature was around 13°C with average precipitation of 117 cm, distributed evenly over the course of the year (Hill 1976). Mean annual temperature measured at Jackson, Kentucky, was 13.6°C with an average precipitation total of 122.8 cm (US Climate Data 2019).

Methods

Free-ranging, adult male elk ≥ 2 years of age were immobilized using a rifle-propelled dart (Pneu-dart, Williamsport, PA) containing the immobilization drug Carfentanil citrate (Zoopharm, Fort Collins, CO) at a dosage of 0.01-0.02 mg/kg of estimated body weight (Kreeger and Franzmann 1996). After a local injection of 1ml of 20 mg/ml lidocaine to the mental foramen, one lower incisor (I4) was pulled using a dental elevator for the purposes of age determination through cementum annuli analysis (Linhart

and Knowlton 1967, Fancy 1980). Two year-old male elk darted in the summer were aged by the presence of an erupting I4 tooth. A 2mm ear punch was taken using a TypiFix sample collector (Gene Check, Inc, Greely, Colorado, USA) for genetic analysis. Captured elk were then fitted with an 8000 MGU global positioning system (GPS) collar (Lotek, Newmarket, Ontario, Canada) that acquired geographic locations every two hours. Error rates for this model of GPS collar are quantified in Augustine et al. (2011). Immobilized elk were recovered via a IM injection of the antagonist Naltrexone hydrochloride at a rate of 100 mg/mg of Carfentanil delivered. Elk capture and immobilization procedures were approved under University of Kentucky IACUC protocol # 2010-0726.

Ear punch tissue samples were sent to Wildlife Genetics International (Nelson, British Columbia, Canada) for microsatellite genotyping. Genotyping for individual elk was analyzed and error checked according to Paetkau (2003) at 16 microsatellite markers (BL42, BM203, BM3507, BM4028, BM4107, BM4513, BM6506, BM888, BMC1009, CSSM041, Oar FCB193, INRA107, OvirH, Rt1, Rt13, Rt7). Of the 305 tissue samples sent to the lab, representing all elk handled for multiple elk ecology projects, 2% lacked sufficient material for analysis, 1% percent failed during genotyping and 97% were successfully genotyped. The genepop package (Rousset 2008), implemented using the R statistical package (Team 2012) was used to test for deviations from Hardy-Weinberg equilibrium and to identify linkage disequilibrium after the application of a Bonferroni sequential correction (Rice 1989). The program ML-relate (Kalinowski et al. 2006) was used to calculate genetic relatedness (Rxy) between elk pairs using maximum likelihood methods (Milligan 2003). With Rxy represented as a value between 0 and 1, and following the guidance of Queller and Goodnight (1989), we chose to group elk pairs into three

categories based on relatedness: unrelated (Rxy = 0-0.25), 2nd order relatives (Rxy > 0.26-0.50) and 1st order relatives (Rxy > 0.50). In our case, working with only male elk, 1st order relatives would be either brothers or a parent/offspring relationship, while 2nd order relatives would be half siblings or a grandfather/grandson relationship (Queller and Goodnight 1989, Magle et al. 2013).

Elk locations were compiled into a location database and subsampled at 4-hr intervals to reduce temporal correlation for the purposes of building a spatial utilization distribution (Börger et al. 2006, Frair et al. 2010). Using a custom function (Appendix 2), seasonal dates were set and the location database was divided into three seasonal sampling frames: winter (January 1 to March 15), summer (June 1 to July 31) and fall (September 1 to October 31). We chose these seasonal sampling periods to represent times of understood and observed seasonal grouping rates of male elk (Killeen et al. 2014b, Benz et al. 2016). For this study, the winter and summer seasons represent times when male elk would congregate in bachelor herds while the fall season encompassed the rutting period. Time periods not included in the above seasons represented intervals of transition between rutting activity and social grouping (Killeen et al. 2014b, Benz et al. 2016) and were not included to reduce noise in the data. For example, during the months of November and December, males are in the post-rut period, but were not observed to be fully grouped up in winter bachelor groups until mid-January (Killeen et al. 2014b). Alternatively, the month of August represented a period where males dissolve bachelor groups in response to an increase in rutting activity (Geist 2002). These seasonal data sets were then categorized by year (2011, 2012, 2013) due to the need to match animals that were alive

and radio-marked in each season/year data set. Annual data frames were then pooled by season.

We constructed space use utilization distributions for all elk in each seasonal data set using the kernalUD function from the adehabitatHR package (Calenge 2006). Volume of Intersection (VI) was calculated as the overlap of two 95% kernel density utilization distributions and represents our measure of spatial overlap (Millspaugh et al. 2004, Schauber et al. 2007, Magle et al. 2013). A VI measurement was produced for each elk pair using the kerneloverlaphr function in the adehabitatHR package (Calenge 2006). VI and genetic relatedness were merged for each season data set and the age difference between each elk pair was calculated. Within each seasonal dataset and across a pooled dataset of all elk pairs combined from each season and year, we used qqplot in the car package (Fox and Weisberg 2019) and the find_skewness function from the dlookr package (Ryu 2019) to test for normality in the VI and Rxy measurements. Scatter plots evaluating the interaction of VI and Rxy were produced using the ggboxplot and ggscatterplot functions in the ggpubr package (Kassambara 2019). Linear mixed effects models using maximum likelihood estimation were applied to the following global model for all seasons and for the pooled elk pairs using the lmer function in the Lme4 package (Bates et al. 2015) including a logit transformation on VI and Rxy:

Model 1: VI ~ Rxy + relatedness group + age difference + (1|id)

Within the global model, fixed effects included genetic relatedness (Rxy), relatedness group and age difference of each elk pair while the random effect is the individual elk.

Likelihood ratio tests were applied to the individual elk random effect using the rand function from the lmerTest package (Kuznetsova et al. 2017). The top model was selected using Akaike's Information Criterion (Akaike 1973, Symonds and Moussalli 2011). Using the dredge function in the MuMIn package (Barton 2018), we selected the top model as that model with an ΔAIC of 0.00 unless that model did not include any variables. While AIC allows researchers to compare and average multiple models, we chose not to employ any form of model averaging per Symonds and Moussalli (2011). We concluded by evaluating the top model with the random effect using the lmer function in the Lme4 package (Bates et al. 2015).

Results

Prior to examining the interaction of genetic relatedness and space use overlap, Hardy-Weinberg probability tests indicated no deviation from Hardy-Weinberg equilibrium ($X^2 = 30.88$, $p = 0.52$). Following Bonferroni sequential correction, three of 120 loci pairs (2.5%) were detected to be in linkage disequilibrium (BM4028:BM6506, BM203:BMC1009, BL42:FCB193). In total, 46 adult male elk contributed location data and genetic relatedness information to this study. Seasonally, 42 elk contributed to the fall season where I observed the lowest mean relatedness (Rxy) value (0.07, SE = 0.01, Table 5.1) and the lowest mean volume of intersection (VI) values (0.09, SE = 0.01). During the summer season, 45 elk presented a mean Rxy of 0.07 (SE=0.00) and a mean VI of 0.12 (SE = 0.01), representing a middle range between the fall and winter seasons. The winter season contributed our highest seasonal mean values of both Rxy (0.08, SE = 0.01) and VI (0.12, SE = 0.01). The summer season had the highest number of 2^{nd} order (N = 32) and 1^{st} order (N = 7) related individuals.

When examining the linear relationship between VI and Rxy, I observed a slight positive relationship in fall (Figure 5.2) and summer (Figure 5.3) and a more pronounced negative relationship in the winter season (Figure 5.4). All seasonal linear relationships lacked explanatory power as defined by an R^2 value less than 0.1. The linear relationship between VI and Rxy for the pooled group was nearly flat, with an R^2 value of -0.000004 (Figure 5.5). According the AIC values, the top model for the fall, summer and pooled seasonal groups, contained no variables (table 5.2). When examining the second best model for these seasons, a model containing relatedness group was identified for the fall season (ΔAIC = 1.08) and the summer season (ΔAIC = 4.54). For the pooled seasons group, the second best model included age difference (ΔAIC = 5.28). The winter season's top model included age difference with a ΔAIC value of 0.00. A likelihood ratio test applied to the random effect of individual elk proved to be significant for all seasonal models, as well as for the pooled season cohort; consequently, the random effect of individual elk remained in all final models.

During the fall season, male elk of 1st order (OR = 1.58, CI = 0.68-2.48) and 2nd order (OR = 1.47, CI = 1.04-1.90) relatedness had higher levels of overlap than unrelated male elk (Table 5.3). Predictive confidence of both estimates in the fall model are low due to the wide confidence intervals and the percent of variation explained by the random effect (22.41%, SE = 0.47). Volume of intersection was greater for 1st order (OR = 1.07, CI = 0.10-2.03) and 2nd order (OR = 1.08, CI = 0.61-1.55) during the summer season, yet the predictive power was again low due to the wide confidence limits that overlapped zero and the percent of variation explained by the random effect (37.08%, SE = 0.61; Table 5.3). The predictive properties of the winter model were much higher than those of the fall and

summer models, yet over 47% of the model variation can be explained by the random effect (47.35%, SE = 0.69). In the winter season, as age difference increased, so too did VI values (OR = 1.20, CI = 1.05-1.36). Age difference had a slight positive correlation with VI in the pooled seasons model (OR = 1.04, CI = 0.98-1.10), while the random effect of individual elk accounted for 28% of the variation in the model (27.94%, SE = 0.53).

Discussion

I examined the relationship between space use, measured as VI (Seidel 1992, Millspaugh et al. 2004), and genetic relatedness (Rxy) between male elk pairs in southeast Kentucky. For the fall season, I correctly hypothesized that we would observe a lower mean VI value and an inverse relationship between VI and Rxy due to the intraspecific competition between male elk for breeding rights (Geist 2002). I was incorrect on the second hypothesis concerning the fall season where we observed a slight positive relationship between VI and Rxy in light of poor predictive power. Additionally in the fall season, model selection indicated relatedness group as a good predictor of VI, yet this trend too, was positive for 1st and 2nd order groups. These results are contrary to what might be expected following dispersal driven by the need to avoid inbreeding (Gasaway et al. 1980, Greenwood 1980, Wolff et al. 1988), as well as the evolutionary forces limiting breeding competition between kin (Hamilton and May 1977). Two issues reduce our clarity of the relationship between VI and Rxy during the fall rutting period: (1) the non-migratory nature of Kentucky elk, and (2) our lack of an understanding of dispersal influences acting on male elk in Kentucky. First, no research has been conducted on the dispersal of male elk within an established herd in the east. Instead, most research on eastern elk has centered on dispersal movements immediately post-translocation (Larkin et

al. 2002, Larkin et al. 2004, Smith et al. 2019). In most migratory western elk populations, dispersal of juvenile male elk is catalyzed by the end of the spring migration (Petersburg et al. 2000, Smith and Anderson 2001, Killeen et al. 2014b). The need to migrate to avoid bad weather or excessive snow pack depth is not present within the Kentucky elk restoration zone and suitable resources are relatively evenly distributed across our study area (Chapter 2). With Kentucky cow elk herds showing strong affinity for specific locations (Slabach 2018), male elk may only need to disperse a short distance to avoid inbreeding and breeding competition with relatives. Future research should include a classic dispersal study where 1.5 year-old male elk are captured in winter and tracked through the dispersal period ultimately determining where they reside during the fall rut.

The age difference between elk pairs was hypothesized to be a poor predictor of VI due to the harem structure and competing interests for breeding rights (Geist 2002). As in other ungulate populations, male elk across adult age classes participate in the rut (Geist 2002). Most observed harems in Kentucky were tended by a dominant male, yet younger male "satellite" elk orbited the harem looking to make a challenge for dominance or steal a female for themselves. This interaction results in shared space for all age classes of adult male elk during the rut, as mirrored by my results.

Following the fall rutting period, male elk segregate themselves and recover from the stressors of the rut (Geist 2002). I chose to delineate seasons based on periods of known male elk aggregation and rutting activity (Geist 2002, Killeen et al. 2014b, Benz et al. 2016). The months of November and December were not considered in this analysis due to our observations that these months were a transitional period between the rut and the formation of winter bachelor groups. I hypothesized that male elk would aggregate with

like-aged males and that Rxy would be a good predictor of VI. Model selection indicated that the age difference between elk pairs was significant in the prediction of VI, but the response was positive, indicating that elk pairs with a greater age difference were more likely to share space. Anecdotally, I commonly observed bachelor groups of mixed age elk ranging in age from 1.5 years old to fully mature elk. I did not expect this due to the findings of Weckerly (2001) where he observed older male elk living in solitude or in loose groups of like-aged individuals, yet my results indicated the highest mean VI occurred in winter.

If I assume that these winter bachelor groups are composed of male elk that occupy a similar area during the rut (i.e. non-migratory) and are interacting to continue or revise a previously held dominance hierarchy ((Weckerly 2001, Geist 2002, Vander Wal et al. 2013), I would conclude that the need to limit breeding competition among kin (Hamilton and May 1977, Kisdi 2016) would limit related male elk from sharing space. Although model selection did not indicate Rxy as a good predictor of VI (Table 5.2), I did observe a negative relationship between VI and Rxy (Figure 5.4), indicating that Rxy has some level of influence over the composition of winter bachelor groups, findings similar to Vander Wal et al. (2012a) who found that proximity-collar-measured direct interactions were not linearly related to Rxy. As such, I conclude that winter bachelor groups were not structured by elk age or genetic relatedness.

With sparring matches peaking just prior to antler casting (Geist 2002), male elk continue to maintain dominance hierarchies through late winter and spring (Weckerly 2001, Geist 2002, Chapman et al. 2003). During the summer season, it is expected that male elk will forgo dominance contests and prioritize nutrient intake (Main et al. 1996,

Geist 2002). Concurrently, I hypothesized that male elk would aggregate and share space regardless of age and Rxy. I observed a nearly flat relationship between VI and Rxy (R^2 = 0.0006; Figure 5.3), thereby supporting my hypothesis. The top model for this season indicated the inclusion of zero variables, so I ran the 2nd best model that included relatedness group. This second model was 4.54 AIC units removed from the top model, and may have questionable utility (Symonds and Moussalli 2011).

Poor predictive qualities of the linear relationship between VI and Rxy precluded any strong conclusions as to the relationship between space use and genetic relatedness among male elk in Kentucky. Relatedness group was included in the second best model of both fall (ΔAIC = 1.08) and summer (ΔAIC = 4.54), while age difference was included in the top model for winter (ΔAIC = 0.00). These results were likely impacted by the number of GPS radio-marked male elk in each season of each year. A mark-resight project including the marked elk used in this project, as well as other VHF radio-marked male elk, indicated a male population of 210 and 174 in August of 2012 and 2013, respectively. Given my sample size in the fall of 2012 (N = 20) and 2013 (N = 17), I calculate that GPS collars were installed on 9.5% of adult male elk in the study area in 2012 and 9.7% in 2013. Patterns of genetic relatedness and space use associated within the vhf radio-marked elk may have tightened up the data and present stronger correlations, but I did not acquire spatial locations on these VHF collared animals used primarily for survival monitoring. The work of Gregory et al. (Gregory et al. 2009) used a relatedness value derived from elk scat to investigate male elk aggregation and sexual segregation, and may represent a template for future research.

Acknowledgements

This research was funded by grants from the federal McIntire-Stennis program, Pitman-Robertson (PR) funds administered by the Kentucky Department of Fish and Wildlife Resources, and a Project Acquisition Committee grant through the Rocky Mountain Elk Foundation.

Table 5.1. Univariate statistics for the analysis of space use measured with volume of interection (VI) and genetic relatedness (Rxy) of bull elk in Kentucky. Rxy was further grouped into relatedness groups. The fall, summer and winter seasons examined radio-marked adult male elk that were observed between 2011-2013. The pooled group represents male elk pairs from all years and seasons.

		Relatedness(Rxy)		Volume of Intersection		Age Difference		Relatedness Group (N)		
Seasons	N	Mean	SE	Mean	SE	Mean	SE	Unrelated	2nd Order	1st Order
Fall	42	0.066	0.005	0.087	0.006	1.525	0.057	464	29	6
Summer	45	0.067	0.004	0.107	0.008	1.473	0.055	495	32	7
Winter	31	0.076	0.006	0.120	0.011	1.242	0.057	303	25	6
Pooled	46	0.069	0.003	0.103	0.005	1.453	0.033	1262	86	19

Table 5.2. Predicitve linear mixed-effects models examinging the relationship between volume of intersection (VI), genetic relatedness (Rxy), relatedness group (rgroup) and the age difference between male elk pairs (agediff) in Kentucky. These models also included the random effect of individual elk [(1|id)]. The fall, summer and winter seasons examined radio-marked adult male elk that were observed between 2011 and 2013. The pooled group represents elk from all years and seasons. Models were evaluated using ΔAIC with the top model in grey highlighting.

Dataset	Model	Log Likelihood	AIC	Δ AIC
Fall	No Model	-776.617	1559.3	0.00
	vi ~ rgroup + (1|id)	-775.122	1560.4	1.08
Summer	No Model	-911.666	1829.4	0.00
	vi ~ rgroup + (1|id)	-911.900	1833.9	4.54
Winter	vi ~ agediff + (1|id)	-594.922	1198.0	0.00
	No Model	-596.009	1198.1	0.13
Pooled	No Model	-2296.246	4598.5	0.00
	vi ~ agediff + (1|id)	-2298.151	4604.3	5.28

Table 5.3. Parameter estimates for the linear mixed-effects models used to examine the relationship between volume of intersection (VI), genetic relatedness (Rxy), relatedness group (rgroup) and the age difference between male elk pairs in Kentucky. The fall, summer and winter seasons examined radio-marked adult male elk that were observed between 2011-2013. The pooled group represents elk from all years and seasons. Parameter estimates were converted to odds ratios with a 95% confidence interval to aid in interpretation.

Dataset	Variable	Estimate	SE	P Value	Odds Ratio	OR 95% CI
Fall	Intercept	-2.759	0.094			
	rgroup: 1st order	0.457	0.459	0.320	1.58	0.68-2.48
	rgroup: 2nd order	0.386	0.218	0.077	1.47	1.04-1.90
Summer	Intercept	-2.660	0.113			
	rgroup: 1st order	0.066	0.493	0.894	1.07	0.10-2.03
	rgroup: 2nd order	0.080	0.241	0.739	1.08	0.61-1.55
Winter	Intercept	-2.721	0.183			
	Age Difference	0.184	0.079	0.020	1.20	1.05-1.36
Pooled	Intercept	-2.730	0.101			
	Age Difference	0.035	0.031	0.248	1.04	0.98-1.10

Figure 5.1. Map of the elk restoration zone and our elk study area (black box) in southeastern Kentucky. We captured and radio-marked adult, male elk across a matrix of active and reclaimed surface mines and forested properties.

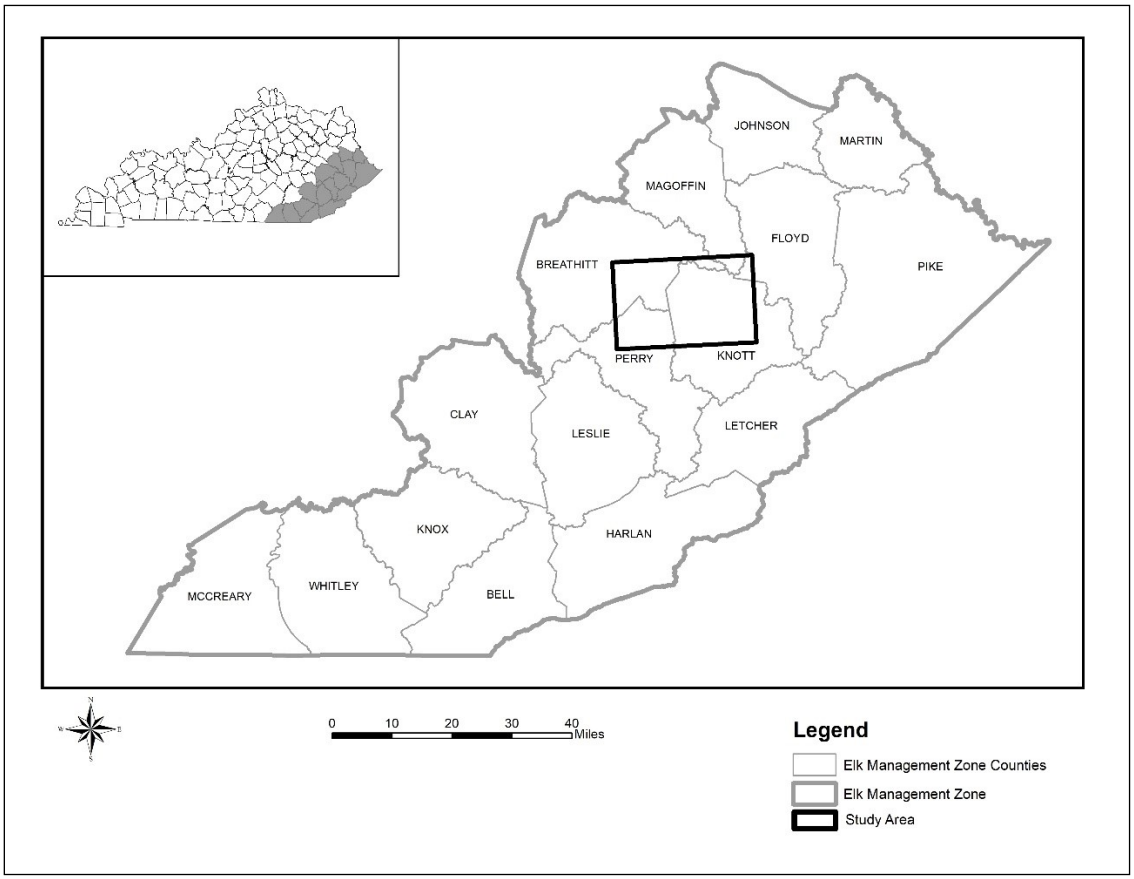


Figure 5.2. The relationship between volume of intersection (VI) and genetic relatedness (Rxy) for male elk in Kentucky during fall. VI was based on the overlap of a utilization distribution while Rxy was determined by genetic analysis at 16 microsatellite markers. Data were pooled from elk pairs observed during one or more years between 2011-2013.

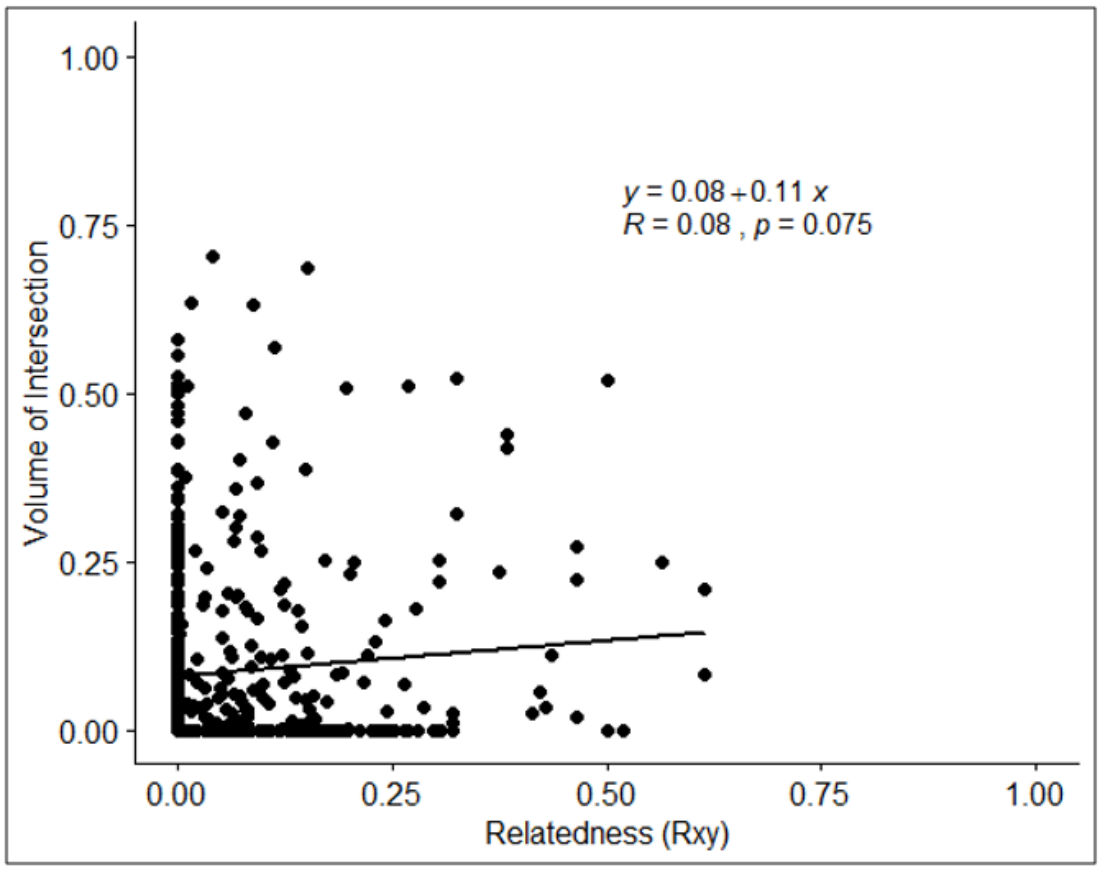


Figure 5.3. The relationship between volume of intersection (VI) and genetic relatedness (Rxy) for male elk in Kentucky during summer. VI was based on the overlap of a utilization distribution while Rxy was determined by genetic analysis at 16 microsatellite markers. Data were pooled from elk pairs observed during one or more years between 2011-2013.

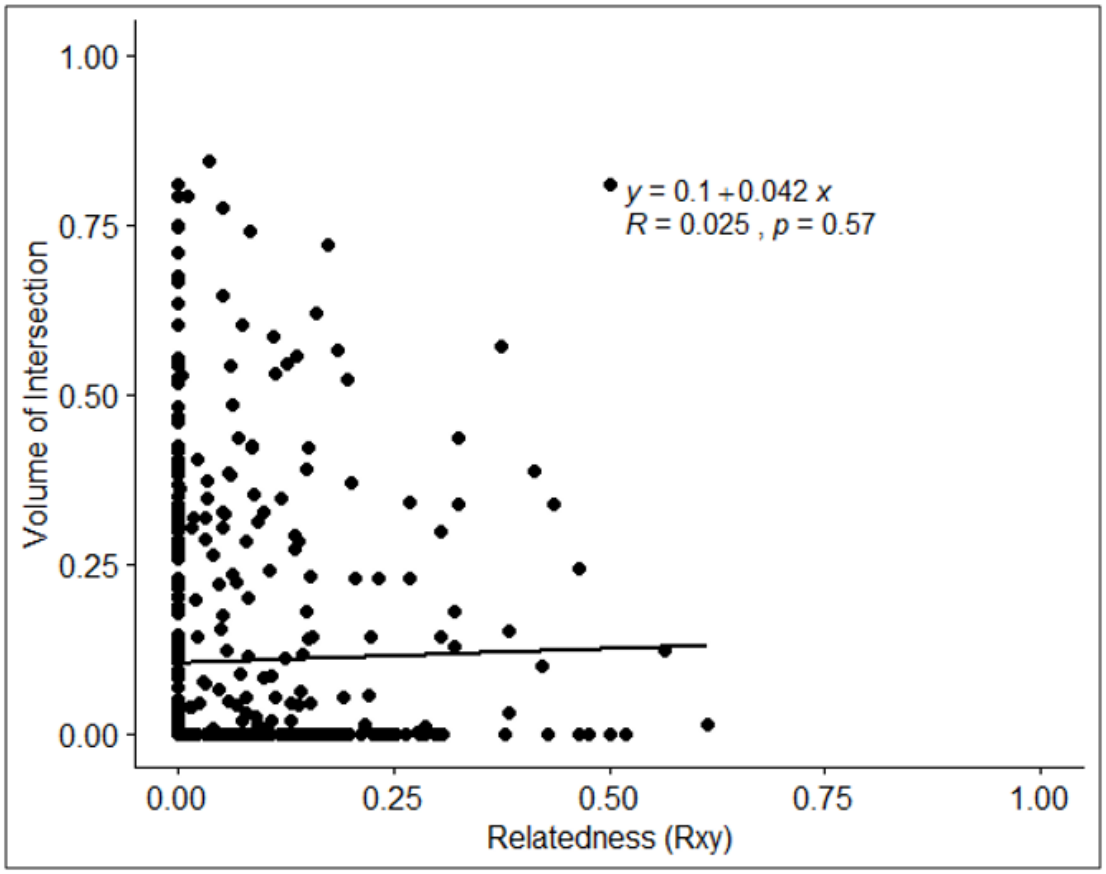


Figure 5.4. The relationship between volume of intersection (VI) and genetic relatedness (Rxy) for male elk during winter. VI was based on the overlap of a utilization distribution while Rxy was determined by genetic analysis at 16 microsatellite markers. Elk for the winter season were pooled from elk pairs observed during one or more years between 2011-2013.

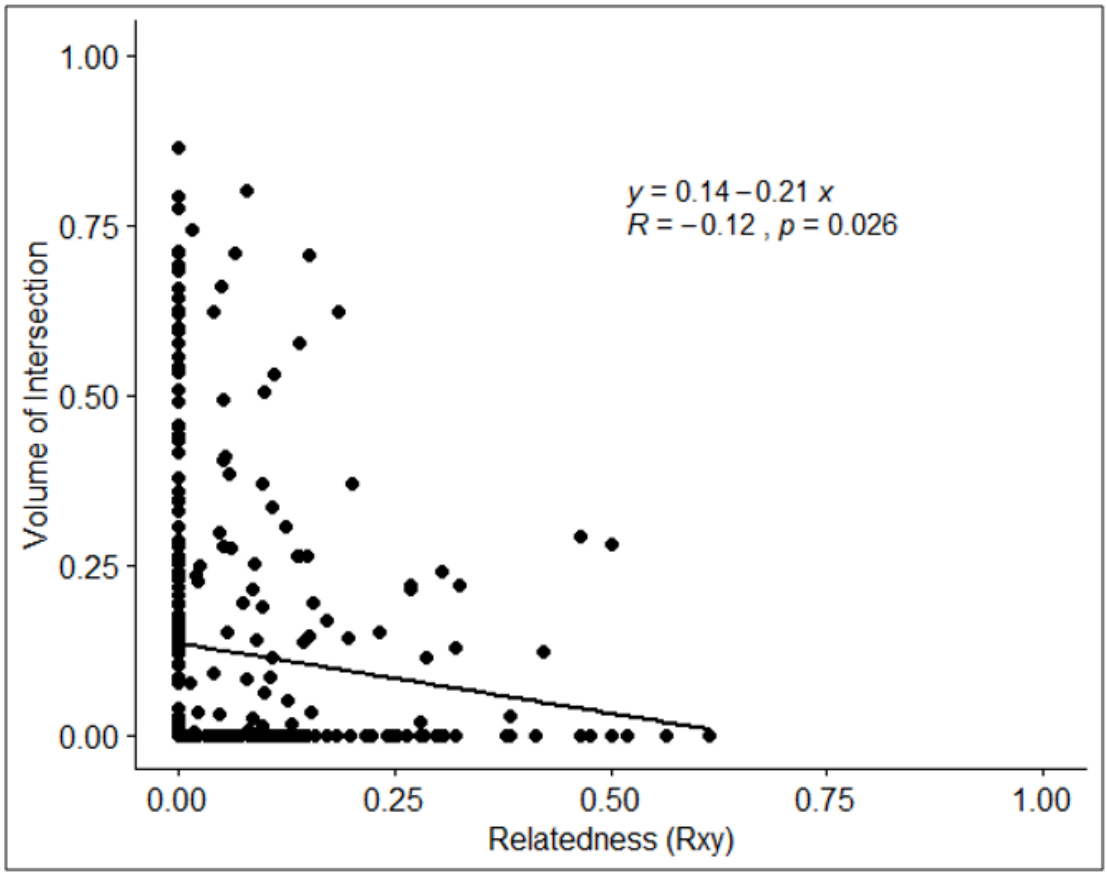
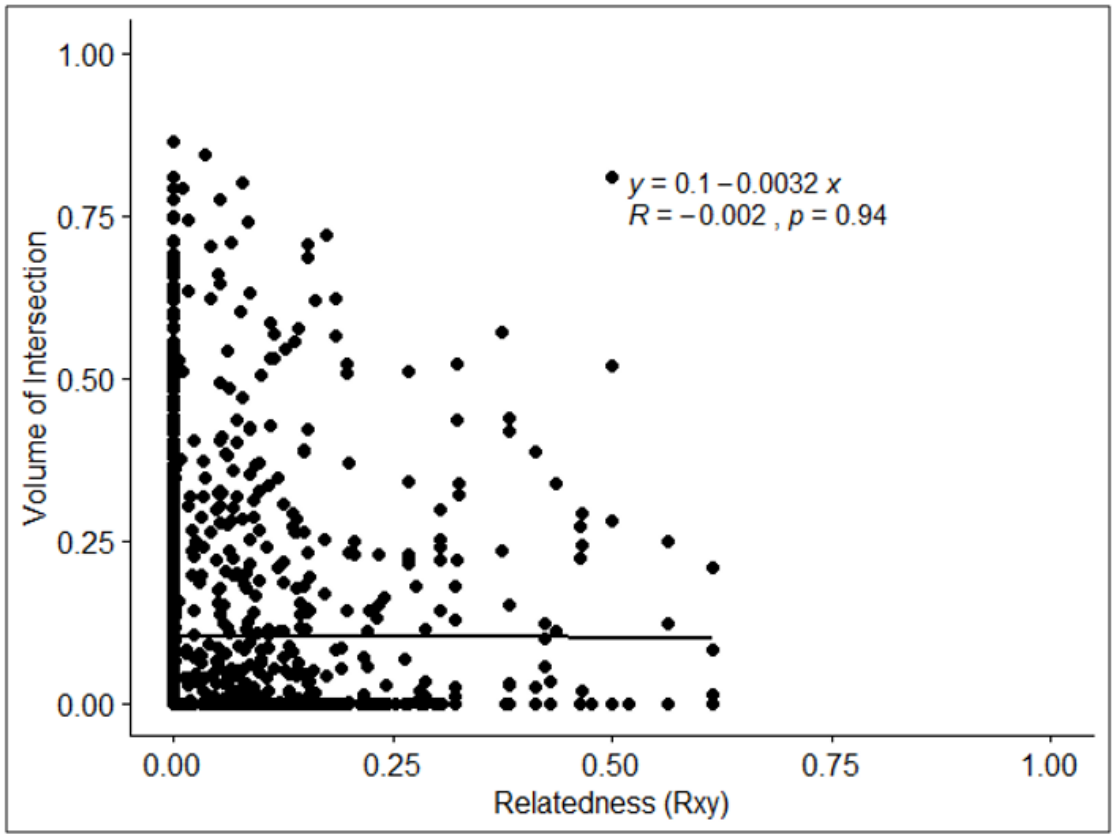


Figure 5.5. The relationship between volume of intersection (VI) and genetic relatedness (Rxy) for male elk in Kentucky pooled across all seasons and years 2011-13. VI was based on the overlap of a utilization distribution while Rxy was determined by genetic analysis at 16 microsatellite markers.



APPENDIX 1. SURVIVAL AND CAUSE –SPECIFIC MORTALITY DATA

Elk ID #	Capture Date	Mortality Date	Cause-specific Mortality	Location	Age at Capture
001	2/2/2011	10/5/2013	gun hunter harvest	Hazard	3
002	1/31/2011	9/28/2011	confirmed p tenuis	Hazard	2
003	2/1/2011	10/8/2012	gun hunter harvest	Hazard	3
004	2/2/2011	9/21/2011	bow hunter harvest	Hazard	2
005	2/3/2011	10/1/2011	gun hunter harvest	Hazard	4
006	2/3/2011	9/21/2011	bow hunter harvest	Hazard	2
007	2/3/2011	10/8/2012	wounding loss	Hazard	2
008	2/3/2011	11/1/2011	bow hunter harvest	Hazard	3
009	1/6/2011	2/15/2011	unknown	Begley	7
011	1/23/2011	-	-	Begley	7
012	1/23/2011	10/10/2012	gun hunter harvest	Begley	5
013	1/24/2011	1/10/2012	confirmed p tenuis	Begley	2
014	1/25/2011	10/5/2013	gun hunter harvest	Begley	4
015	2/3/2011	-	-	Hazard	2
016	1/7/2011	8/1/2011	probable p tenuis	Begley	5
017	3/16/2011	-	-	Hazard	2
018	2/4/2011	9/18/2011	bow hunter harvest	Hazard	2
019	2/10/2011	10/12/2013	gun hunter harvest	Hazard	4
020	2/3/2011	3/30/2011	probable p tenuis	Hazard	2
021	2/4/2011	-	-	Hazard	4
022	2/4/2011	9/22/2012	bow hunter harvest	Hazard	4
023	2/3/2011	9/16/2012	fence kill	Hazard	2
024	2/1/2011	9/25/2013	bow hunter harvest	Hazard	3
025	2/1/2011	9/30/2012	bow hunter harvest	Hazard	2
026	2/24/2011	10/6/2012	gun hunter harvest	Begley	2
027	2/14/2011	9/17/2012	bow hunter harvest	Begley	3
028	2/9/2011	9/29/2012	gun hunter harvest	Hazard	2
029	2/5/2011	9/15/2012	bow hunter harvest	Hazard	3
031	3/3/2011	10/7/2012	gun hunter harvest	Hazard	2
032	2/10/2011	8/13/2011	probable p tenuis	Hazard	2
033	2/8/2011	8/31/2011	confirmed p tenuis	Hazard	4
034	2/5/2011	9/17/2011	bow hunter harvest	Hazard	2
035	2/9/2011	11/26/2011	bow hunter harvest	Hazard	3
036	3/1/2011	censor	dropped collar	Hazard	3
037	2/15/2011	10/2/2011	gun hunter harvest	Begley	2
038	2/28/2011	9/29/2012	gun hunter harvest	Hazard	5

039	2/16/2011	12/10/2012	wounding loss	Begley	4
040	2/21/2011	-	-	Begley	2
041	3/3/2011	12/29/2012	bow hunter harvest	Hazard	3
042	2/18/2011	-	-	Begley	2
043	2/28/2011	censor	dropped collar	Hazard	5
045	3/9/2011	10/4/2013	probable p tenuis	Hazard	4
047	3/9/2011	11/26/2011	bow hunter harvest	Hazard	2
048	3/2/2011	7/13/2012	probable p tenuis	Pike	10
049	3/4/2011	10/11/2011	gun hunter harvest	Pike	3
050	3/7/2011	9/17/2012	bow hunter harvest	Hazard	2
051	3/11/2011	10/4/2012	road kill	Hazard	2
052	3/9/2011	-	-	Hazard	2
053	3/10/2011	9/19/2011	bow hunter harvest	Hazard	3
054	3/14/2011	11/22/2012	bow hunter harvest	Hazard	2
055	3/10/2011	10/17/2012	gun hunter harvest	Hazard	2
056	3/10/2011	10/6/2012	gun hunter harvest	Hazard	3
057	3/11/2011	-	-	Hazard	2
058	3/12/2011	10/26/2012	fence kill	Hazard	2
059	3/14/2011	10/7/2012	gun hunter harvest	Hazard	3
060	3/14/2011	9/17/2012	bow hunter harvest	Hazard	2
061	2/16/2012	10/7/2013	gun hunter harvest	Hazard	3
062	1/19/2012	10/5/2013	gun hunter harvest	Hazard	1
063	1/20/2012	10/17/2012	gun hunter harvest	Hazard	3
064	2/16/2012	10/11/2013	gun hunter harvest	Hazard	4
065	2/15/2012	10/8/2013	gun hunter harvest	Hazard	2
066	1/16/2012	-	-	Begley	3
067	2/16/2012	9/24/2012	bow hunter harvest	Hazard	2
068	2/17/2012	9/24/2012	bow hunter harvest	Begley	2
069	1/20/2012	-	-	Hazard	2
070	2/17/2012	-	-	Begley	2
071	3/8/2012	10/18/2012	gun hunter harvest	Hazard	3
072	5/17/2012	11/1/2013	interspecific kill	Pike	5
073	3/4/2012	10/15/2012	gun hunter harvest	Hazard	3
074	3/1/2012	10/14/2012	gun hunter harvest	Hazard	8
075	2/29/2012	10/13/2012	gun hunter harvest	Hazard	2
076	3/2/2012	10/27/2012	poaching case	Hazard	2
077	2/23/2012	10/10/2013	wounding loss	Hazard	3
078	2/20/2012	10/7/2012	wounding loss	Hazard	3
079	2/15/2012	7/26/2012	confirmed p tenuis	Hazard	2
080	2/15/2012	10/7/2012	gun hunter harvest	Hazard	4
081	3/7/2012	12/21/2012	stuck in sludge pond	Hazard	3
082	2/16/2012	-	-	Hazard	3

083	2/16/2012	-	-	Hazard	5
085	3/5/2012	11/22/2012	bow hunter harvest	Hazard	2
086	2/23/2012	10/13/2013	gun hunter harvest	Begley	3
087	3/2/2012	-	-	Hazard	5
088	3/3/2012	-	-	Hazard	3
089	2/23/2012	9/17/2012	bow hunter harvest	Hazard	4
090	2/21/2012	10/9/2012	gun hunter harvest	Hazard	6
091	2/21/2012	12/6/2012	bow hunter harvest	Hazard	12
092	2/20/2012	10/7/2013	wounding loss	Hazard	3
093	6/13/2012	11/1/2013	wounding loss	Hazard	3
094	3/22/2012	10/5/2013	gun hunter harvest	Hazard	2
095	2/22/2012	12/9/2013	bow hunter harvest	Hazard	2
096	2/28/2012	10/8/2012	gun hunter harvest	Hazard	3
097	3/28/2012	9/17/2012	bow hunter harvest	Hazard	2
098	6/20/2012	10/12/2013	gun hunter harvest	Hazard	2
099	6/20/2012	censor	dropped collar	Hazard	6
100	7/18/2012	-	-	Hazard	6
101	7/13/2012	-	-	Hazard	3
102	7/11/2012	-	-	Hazard	9
103	7/13/2012	-	-	Hazard	4
104	7/13/2012	censor	dropped collar	Hazard	4
105	7/17/2012	10/9/2013	wounding loss	Hazard	4
106	6/19/2012	10/13/2012	gun hunter harvest	Hazard	2
107	6/5/2012	9/20/2012	wounding loss	Hazard	3
108	6/5/2012	9/20/2012	bow hunter harvest	Hazard	6
109	2/20/2012	9/27/2012	bow hunter harvest	Hazard	2
110	2/27/2012	10/6/2013	gun hunter harvest	Hazard	5
111	6/6/2012	1/18/2013	bow hunter harvest	Hazard	2
112	6/6/2012	10/18/2013	gun hunter harvest	Hazard	3
113	7/18/2012	10/16/2013	road kill	Hazard	2
114	6/5/2012	-	-	Hazard	3
115	4/5/2012	10/13/2012	gun hunter harvest	Hazard	2
116	4/4/2012	7/22/2013	probable p tenuis	Hazard	3
117	6/14/2012	12/16/2012	confirmed p tenuis	Hazard	1
118	7/17/2012	10/28/2012	bow hunter harvest	Hazard	2
119	2/27/2012	10/13/2012	wounding loss	Hazard	2
120	2/21/2012	10/6/2012	gun hunter harvest	Hazard	2
121	7/8/2013	-	-	Hazard	2
122	3/7/2013	-	-	Hazard	2
123	3/13/2013	5/2/2013 censor	dropped collar	Hazard	3
125	3/1/2013	-	-	Hazard	6
126	3/1/2013	11/5/2013	unknown	Hazard	4

127	7/9/2013	-	-	Hazard	5
128	3/23/2013	10/8/2013	gun hunter harvest	Hazard	2
129	3/28/2013	10/18/2013	interspecific kill	Hazard	2
130	2/23/2013	-	-	Hazard	5
132	7/16/2013	9/21/2013	bow hunter harvest	Hazard	2
133	6/21/2013	-	-	Hazard	2
134	6/18/2013	-	-	Hazard	4
135	6/14/2013	9/21/2013	wounding loss	Hazard	3
136	5/30/2013	-	-	Hazard	3
137	6/4/2013	10/13/2013	gun hunter harvest	Hazard	5
138	6/18/2013	-	-	Hazard	2
139	5/31/2013	-	-	Hazard	2
140	7/10/2013	-	-	Hazard	1
141	3/28/2013	-	-	Hazard	3
142	2/14/2013	11/15/2013	unknown	Hazard	4
143	6/5/2013	-	-	Hazard	2
144	2/9/2013	-	-	Hazard	5
145	1/19/2013	10/4/2013	wounding loss	Begley	3
146	1/18/2013	-	-	Begley	5
147	1/18/2013	-	-	Begley	4
149	2/21/2013	4/3/2013	probable p tenuis	Hazard	3
150	2/20/2013	-	-	Hazard	3
151	1/29/2013	-	-	Begley	5
152	1/21/2013	10/14/2013	gun hunter harvest	Begley	3
153	1/25/2012	8/30/2013	probable p tenuis	Begley	3
158	6/10/2013	9/22/2013	bow hunter harvest	Hazard	4
159	6/18/2013	10/11/2013	gun hunter harvest	Hazard	6
160	6/18/2013	2/1/2014	road kill	Hazard	3
162	6/10/2013	-	-	Hazard	4
163	2/7/2013	-	-	Hazard	2
164	3/29/2013	9/17/2013	road kill	Hazard	4
165	2/19/2013	-	-	Hazard	3
166	2/10/2013	-	-	Hazard	2
167	3/8/2013	-	-	Hazard	2
168	3/28/2013	-	-	Hazard	3
169	3/21/2013	10/13/2013	gun hunter harvest	Hazard	2
170	3/23/2013	10/15/2013	gun hunter harvest	Hazard	4
172	6/14/2013	-	-	Hazard	4
173	3/24/2013	9/28/2013	bow hunter harvest	Hazard	4
174	2/23/2013	11/1/2013	wounding loss	Hazard	2
175	2/5/2013	-	-	Hazard	4
176	6/11/2013	-	-	Hazard	5

177	2/13/2013	11/7/2013	bow hunter harvest	Hazard	2
178	2/20/2013	-	-	Hazard	2
179	1/30/2013	-	-	Begley	2
G1718	7/23/2012	9/20/2012	bow hunter harvest	Hazard	2
Y2	7/19/2012	10/13/2012	gun hunter harvest	Hazard	5
Y3	7/28/2011	censor	dropped collar	Hazard	4
Y4/084	3/15/2011	11/4/2012	bow hunter harvest	Hazard	2
Y5	3/15/2011	11/8/2012	unknown	Hazard	2
Y6	3/15/2011	9/21/2012	bow hunter harvest	Hazard	4
Y7	6/15/2011	10/13/2012	gun hunter harvest	Hazard	3
Y8	7/10/2012	10/7/2012	gun hunter harvest	Hazard	3

APPENDIX 2. RESOURCE SELECTION FUNCTION CODE

```
# Title: Elk_RSF_Hast.R "Elk Resource Selection Function - Hast version"
# Project: Hast dissertation

library(lubridate)     # as.POSIXct() time manipulation
library(maptools)      # sunriset(), solarnoon() in custom function emphemeris()
library(rgdal)         # writeOGR
library(raster)        # do.call()
library(plyr)          # %>% operations, filter()
library(dplyr)         # %>% operations, filter()
library(sp)            # SpatialPointsDataFrame()
library(adehabitatHR)  # mcp() generate home ranges
library(lme4)
library(AICcmodavg)
library(car)
library(psych)
library(MuMIn)         #dredge
library(sf)           #predictive raster - I need to install this later in the code!!!
library(boot)
library(FedData)      #landsat import

# 1. Load data ####
setwd("O:/Hast/UK RESEARCH/Resource use working folder/landsat")
getwd()
df = read.csv('elklocs.csv') # change to your master CSV with ALL locations
head(df)

#------------------------------------------------------------------------------#

# 2. Clean data ####
# 2.1. Omit  pseudo-absences ####
# used Type = 0 for absence, and Type = 1 for presence.
df = df[ df$Type == 1, ]

# 2.2. Convert date.POSIX column from factor to POSIXct ####
df$date = as.POSIXct( strptime(as.character(df$date),
                        format = '%Y-%m-%d %H:%M:%S',
                        tz = 'America/New_York'))

# Season & Daynight Columns ####
# If all you have is a date/time column(s), then those need
# to be categorized by season and day/night.
# I wrote custom functions getSeason and ephemeris to do this.
```

```
#-------------------------------------------------------------------------#

# 3. Label dates and times ####
# 3.1. My custom functions ####
getSeason <- function(DATES) {

  # Categorizes vector DATES into seasons.
  # Returns a vector of character strings.

  Winter <- as.Date("2012-01-01", format = "%Y-%m-%d")
  Interim1 <- as.Date("2012-04-30", format = "%Y-%m-%d")
  Summer <- as.Date("2012-05-01", format = "%Y-%m-%d")
  Interim2 <- as.Date("2012-08-31", format = "%Y-%m-%d")
  Fall <- as.Date("2012-09-01", format = "%Y-%m-%d")
  Interim3 <- as.Date("2012-12-31", format = "%Y-%m-%d")

  # Convert dates from any year to 2012 dates
  d <- as.Date(strftime(DATES, format="2012-%m-%d"))

  ifelse (d >= Winter & d < Interim1, "Winter",
        ifelse (d >= Interim1 & d < Summer, "Interim1",
              ifelse (d >= Summer & d < Interim2, "Summer",
                    ifelse( d >= Interim2 & d < Fall, "Interim2",
                          ifelse( d >= Fall & d < Interim3, "Fall",
                                "Interim3")))))
}
ephemeris <- function(lat, lon, dates) {

  ## Returns dataframe of Sunrise, Sunset, and Solar Noon times
  # at a lat, long location for all dates.

  # convert to the format
  lon.lat <- matrix(c(lon, lat), nrow=1)

  # get sunrise, sunset, and noon times
  sunrise <- sunriset(lon.lat, dates, direction="sunrise", POSIXct.out=TRUE)
  sunset <- sunriset(lon.lat, dates, direction="sunset", POSIXct.out=TRUE)
  solar_noon <- solarnoon(lon.lat, dates, POSIXct.out=TRUE)

  # build a data frame from the vectors
  tempdf = data.frame( date = dates,
                    sunrise = sunrise$time,
                    sunset = sunset$time,
                    noon = solar_noon$time )

  tempdf$daynight = NA
```

```
  tempdf$daynight[ tempdf$date < tempdf$sunrise | tempdf$date >= tempdf$sunset ] =
'night'
  tempdf$daynight[ tempdf$date >= tempdf$sunrise & tempdf$date < tempdf$sunset ] =
'day'

  return(tempdf$daynight)
}

# 3.2. Assign seasons to dates ####
# use custom function getSeason
df$season = getSeason(df$date)
df = df[df$season %in% c('Summer', 'Winter', 'Fall'), ]  # remove out-of season locations
nrow(df)                                    # now only 431,346 rows
df$season = as.factor(df$season)                    # convert season from character to factor
df$season = relevel(df$season, ref = 'Winter')          # set Winter as reference season
table(df$season)                                  # check results

# 3.3. Assign day or night to times ###
# use custom fuction ephemeris
df$daynight = ephemeris(lat = 37.448744, lon = -83.051624, dates = df$date)
df$daynight = as.factor(df$daynight)                  # convert to factor
df$daynight = relevel(df$daynight, ref = 'night')       # set night as reference time
table(df$daynight)                                  # check results

# check results of 25 random locations
df[sample.int(nrow(df), 25), c('date', 'season', 'daynight')]
head(df)

# 3.3. Subset by season & daynight ####
# keeping only X,Y, and ID columns
df_wd = df[ df$season == 'Winter' & df$daynight == 'day', c('X', 'Y', 'ID') ]
df_wn = df[ df$season == 'Winter' & df$daynight == 'night', c('X', 'Y', 'ID')]
df_sd = df[ df$season == 'Summer' & df$daynight == 'day', c('X', 'Y', 'ID')]
df_sn = df[ df$season == 'Summer' & df$daynight == 'night', c('X', 'Y', 'ID')]
df_fd = df[ df$season == 'Fall' & df$daynight == 'day', c('X', 'Y', 'ID')]
df_fn = df[ df$season == 'Fall' & df$daynight == 'night', c('X', 'Y', 'ID')]

# 3.4. Clean up ####
rm(ephemeris, getSeason)

#-----------------------------------------------------------------------------#

# 4. Filter out elk with <5 relocations ####
# mcp() cannot estimate home ranges with <5 relocations
# %>% is called a piping function. requires plyr and dplyr packages.
df_wd = df_wd %>%
```

```
  group_by(ID) %>%
  filter(n() > 5) %>%
  droplevels() %>%
  as.data.frame()
df_wn = df_wn %>%
  group_by(ID) %>%
  filter(n() > 5) %>%
  droplevels() %>%
  as.data.frame()
df_sd = df_sd %>%
  group_by(ID) %>%
  filter(n() > 5) %>%
  droplevels() %>%
  as.data.frame()
df_sn = df_sn %>%
  group_by(ID) %>%
  filter(n() > 5) %>%
  droplevels() %>%
  as.data.frame()
df_fd = df_fd %>%
  group_by(ID) %>%
  filter(n() > 5) %>%
  droplevels() %>%
  as.data.frame()
df_fn = df_fn %>%
  group_by(ID) %>%
  filter(n() > 5) %>%
  droplevels() %>%
  as.data.frame()

class(df_fn) # data.frame

#------------------------------------------------------------------------------#

# 5. Promote to spatial ####

# Coorindate Reference System (CRS) of input data
myCRS = CRS("+proj=utm +zone=17 +datum=NAD83 +units=m +no_defs
+ellps=GRS80 +towgs84=0,0,0")

spdf_wd = SpatialPointsDataFrame(coords = df_wd[,c("X","Y")], data = df_wd,
proj4string = myCRS)
spdf_wn = SpatialPointsDataFrame(coords = df_wn[,c("X","Y")], data = df_wn,
proj4string = myCRS)
spdf_sd = SpatialPointsDataFrame(coords = df_sd[,c("X","Y")], data = df_sd, proj4string
= myCRS)
```

```
spdf_sn = SpatialPointsDataFrame(coords = df_sn[,c("X","Y")], data = df_sn, proj4string
= myCRS)
spdf_fd = SpatialPointsDataFrame(coords = df_fd[,c("X","Y")], data = df_fd, proj4string
= myCRS)
spdf_fn = SpatialPointsDataFrame(coords = df_fn[,c("X","Y")], data = df_fn, proj4string
= myCRS)

# 5.1. Export spdf of locations as a shapefile ####
# This is one single shapefle with all actual locations
writeOGR(spdf_wd, getwd(), "wdac", driver = "ESRI Shapefile")
writeOGR(spdf_wn, getwd(), "wnac", driver = "ESRI Shapefile")
writeOGR(spdf_fd, getwd(), "fdac", driver = "ESRI Shapefile")
writeOGR(spdf_fn, getwd(), "fnac", driver = "ESRI Shapefile")
writeOGR(spdf_sd, getwd(), "sdac", driver = "ESRI Shapefile")
writeOGR(spdf_sn, getwd(), "snac", driver = "ESRI Shapefile")
# this file still had X and Y locations attached

# 5.2. Remove X and Y columns ####
# because mcp() allows only 1 column in SPDF for individual ID
spdf_wd = spdf_wd[,'ID']
spdf_wn = spdf_wn[,'ID']
spdf_sd = spdf_sd[,'ID']
spdf_sn = spdf_sn[,'ID']
spdf_fd = spdf_fd[,'ID']
spdf_fn = spdf_fn[,'ID']

# 5.3. Plot SPDFs ####
# plot(spdf_wd, col = spdf_wd$ID, main = 'Winter Day')
# plot(spdf_wn, col = spdf_wn$ID, main = 'Winter Night')
# plot(spdf_sd, col = spdf_sd$ID, main = 'Summer Day')
# plot(spdf_sn, col = spdf_sn$ID, main = 'Summer Night')
# plot(spdf_fd, col = spdf_fd$ID, main = 'Fall Day')
# plot(spdf_fn, col = spdf_fn$ID, main = 'Fall Night')

#-----------------------------------------------------------------------------#

# 6. MCP Home ranges ####

# 6.1. 90% MCP for Winter/summer/fall
wd_mcp90 = mcp(spdf_wd, percent = 90, unin = 'm', unout = 'm2')
wn_mcp90 = mcp(spdf_wn, percent = 90, unin = 'm', unout = 'm2')
fd_mcp90 = mcp(spdf_fd, percent = 90, unin = 'm', unout = 'm2')
fn_mcp90 = mcp(spdf_fn, percent = 90, unin = 'm', unout = 'm2')
sd_mcp90 = mcp(spdf_sd, percent = 90, unin = 'm', unout = 'm2')
sn_mcp90 = mcp(spdf_sn, percent = 90, unin = 'm', unout = 'm2')
```

```
# 6.2. Plot Home ranges ####

# Winter/summer/fall mcp = 90
#plot(wd_mcp90, border = wd_mcp90$id, main = 'Winter Day 90% MCP')
#plot(wn_mcp90, border = wn_mcp90$id, main = 'Winter Night 90% MCP')
#plot(fd_mcp90, border = fd_mcp90$id, main = 'Fall Day 90% MCP')
#plot(fn_mcp90, border = fn_mcp90$id, main = 'Fall Night 90% MCP')
#plot(sd_mcp90, border = sd_mcp90$id, main = 'Summer Day 90% MCP')
#plot(sn_mcp90, border = sn_mcp90$id, main = 'Summer Night 90% MCP')

# 6.3. Export MCP as shapefile ####

# Winter/summer/fall mcp = 90
writeOGR(wd_mcp90, dsn = getwd(), layer = "wd_mcp90", driver = "ESRI Shapefile")
writeOGR(wn_mcp90, dsn = getwd(), layer = "wn_mcp90", driver = "ESRI Shapefile")
writeOGR(fd_mcp90, dsn = getwd(), layer = "fd_mcp90", driver = "ESRI Shapefile")
writeOGR(fn_mcp90, dsn = getwd(), layer = "fn_mcp90", driver = "ESRI Shapefile")
writeOGR(sd_mcp90, dsn = getwd(), layer = "sd_mcp90", driver = "ESRI Shapefile")
writeOGR(sn_mcp90, dsn = getwd(), layer = "sn_mcp90", driver = "ESRI Shapefile")

#------------------------------------------------------------------------#

# 7. Pseudo-absences ####

# 7.1. Generate pseudo-absences by season ####
# wd
nrow(spdf_wd) # 3006 presence locations
head(wd_mcp90)
levels(wd_mcp90$id)

wd_abs_list = lapply(
  # apply function to each ID
  levels(wd_mcp90$id),
  FUN = function(ID) {
    message(ID)
    # Generate random points
    s = spsample(
      x = wd_mcp90[wd_mcp90$id == ID, ],
      n = 100,
      type = "random",
      iter = 30
    )
    # Convert from SpatialPoints to SpatialPointsDataFrame, and assign elk ID
    s = SpatialPointsDataFrame(s, data = data.frame(id = rep(ID, length(s))))
  }
```

```
  # outputs a list
)

spdf_wd_abs = do.call(rbind, wd_abs_list) # Convert list of SPDFs to one SPDF
table(spdf_wd_abs$id) # check result

# wn
nrow(spdf_wn)
head(wn_mcp90)
levels(wn_mcp90$id)

wn_abs_list = lapply(
  # apply function to each ID
  levels(wn_mcp90$id),
  FUN = function(ID) {
    message(ID)
    # Generate random points
    s = spsample(
      x = wn_mcp90[wn_mcp90$id == ID, ],
      n = 100,
      type = "random",
      iter = 30
    )
    # Convert from SpatialPoints to SpatialPointsDataFrame, and assign elk ID
    s = SpatialPointsDataFrame(s, data = data.frame(id = rep(ID, length(s))))
  }
  # outputs a list
)

spdf_wn_abs = do.call(rbind, wn_abs_list) # Convert list of SPDFs to one SPDF
table(spdf_wn_abs$id) # check result

# fd
nrow(spdf_fd)
head(fd_mcp90)
levels(fd_mcp90$id)

fd_abs_list = lapply(
  # apply function to each ID
  levels(fd_mcp90$id),
  FUN = function(ID) {
    message(ID)
    # Generate random points
    s = spsample(
      x = fd_mcp90[fd_mcp90$id == ID, ],
      n = 100,
```

```
    type = "random",
    iter = 30
   )
   # Convert from SpatialPoints to SpatialPointsDataFrame, and assign elk ID
   s = SpatialPointsDataFrame(s, data = data.frame(id = rep(ID, length(s))))
  }
  # outputs a list
)

spdf_fd_abs = do.call(rbind, fd_abs_list) # Convert list of SPDFs to one SPDF
table(spdf_fd_abs$id) # check result

# fn
nrow(spdf_fn)
head(fn_mcp90)
levels(fn_mcp90$id)

fn_abs_list = lapply(
  # apply function to each ID
  levels(fn_mcp90$id),
  FUN = function(ID) {
    message(ID)
    # Generate random points
    s = spsample(
      x = fn_mcp90[fn_mcp90$id == ID, ],
      n = 100,
      type = "random",
      iter = 30
    )
    # Convert from SpatialPoints to SpatialPointsDataFrame, and assign elk ID
    s = SpatialPointsDataFrame(s, data = data.frame(id = rep(ID, length(s))))
  }
  # outputs a list
)

spdf_fn_abs = do.call(rbind, fn_abs_list) # Convert list of SPDFs to one SPDF
table(spdf_fn_abs$id) # check result

# sd
nrow(spdf_sd)
head(sd_mcp90)
levels(sd_mcp90$id)

sd_abs_list = lapply(
  # apply function to each ID
  levels(sd_mcp90$id),
```

```
  FUN = function(ID) {
    message(ID)
    # Generate random points
    s = spsample(
      x = sd_mcp90[sd_mcp90$id == ID, ],
      n = 100,
      type = "random",
      iter = 30
    )
    # Convert from SpatialPoints to SpatialPointsDataFrame, and assign elk ID
    s = SpatialPointsDataFrame(s, data = data.frame(id = rep(ID, length(s))))
  }
  # outputs a list
)

spdf_sd_abs = do.call(rbind, sd_abs_list) # Convert list of SPDFs to one SPDF
table(spdf_sd_abs$id) # check result

# sn
nrow(spdf_sn)
head(sn_mcp90)
levels(sn_mcp90$id)

sn_abs_list = lapply(
  # apply function to each ID
  levels(sn_mcp90$id),
  FUN = function(ID) {
    message(ID)
    # Generate random points
    s = spsample(
      x = sn_mcp90[sn_mcp90$id == ID, ],
      n = 100,
      type = "random",
      iter = 30
    )
    # Convert from SpatialPoints to SpatialPointsDataFrame, and assign elk ID
    s = SpatialPointsDataFrame(s, data = data.frame(id = rep(ID, length(s))))
  }
  # outputs a list
)

spdf_sn_abs = do.call(rbind, sn_abs_list) # Convert list of SPDFs to one SPDF
table(spdf_sn_abs$id) # check result

# 7.2. Export pseudo-points as shapefile ####
writeOGR(spdf_wd_abs, getwd(), "wd90pseudo", driver = "ESRI Shapefile")
```

```
writeOGR(spdf_wn_abs, getwd(), "wn90pseudo", driver = "ESRI Shapefile")
writeOGR(spdf_fd_abs, getwd(), "fd90pseudo", driver = "ESRI Shapefile")
writeOGR(spdf_fn_abs, getwd(), "fn90pseudo", driver = "ESRI Shapefile")
writeOGR(spdf_sd_abs, getwd(), "sd90pseudo", driver = "ESRI Shapefile")
writeOGR(spdf_sn_abs, getwd(), "sn90pseudo", driver = "ESRI Shapefile")
# this gives us 100 random points for each elk within their respective MCP.
# - checks out

# 7.3. Combine presences and absences  ####
# e.g. spdf_wd and spdf_wd_abs

# 7.3.1. Add column to each indicating type of point (actual vs psuedo)
spdf_wd$type <- 1
spdf_wd_abs$type <- 0
spdf_wn$type <- 1
spdf_wn_abs$type <- 0
spdf_fd$type <- 1
spdf_fd_abs$type <- 0
spdf_fn$type <- 1
spdf_fn_abs$type <- 0
spdf_sd$type <- 1
spdf_sd_abs$type <- 0
spdf_sn$type <- 1
spdf_sn_abs$type <- 0

# 7.3.2. Adjust spdf_wd ID column to match the "id" column of spdf_wd_abs ####
names(spdf_wd)[1] <- "id"
names(spdf_wn)[1] <- "id"
names(spdf_fd)[1] <- "id"
names(spdf_fn)[1] <- "id"
names(spdf_sd)[1] <- "id"
names(spdf_sn)[1] <- "id"

# 7.3.3. Combine spdf_wd and spdf_wd_abs ####
spdf_wd_ap <- rbind(spdf_wd, spdf_wd_abs) #[spdf_wd_ap = file with all points]
spdf_wn_ap <- rbind(spdf_wn, spdf_wn_abs)
spdf_fd_ap <- rbind(spdf_fd, spdf_fd_abs)
spdf_fn_ap <- rbind(spdf_fn, spdf_fn_abs)
spdf_sd_ap <- rbind(spdf_sd, spdf_sd_abs)
spdf_sn_ap <- rbind(spdf_sn, spdf_sn_abs)

head(spdf_wd_ap)
head(spdf_wn_ap)
head(spdf_fd_ap)
head(spdf_fn_ap)
head(spdf_sd_ap)
```

```
head(spdf_sn_ap)

nrow(spdf_wd_ap)
nrow(spdf_wn_ap)
nrow(spdf_fd_ap)
nrow(spdf_fn_ap)
nrow(spdf_sd_ap)
nrow(spdf_sn_ap)

# 7.4. write coords to data slot ####
spdf_wd_ap@data[,c('x','y')] <- coordinates(spdf_wd_ap)
spdf_wn_ap@data[,c('x','y')] <- coordinates(spdf_wn_ap)
spdf_fd_ap@data[,c('x','y')] <- coordinates(spdf_fd_ap)
spdf_fn_ap@data[,c('x','y')] <- coordinates(spdf_fn_ap)
spdf_sd_ap@data[,c('x','y')] <- coordinates(spdf_sd_ap)
spdf_sn_ap@data[,c('x','y')] <- coordinates(spdf_sn_ap)

# 7.5. Write pres+abs points to CSV ####
# write.csv(spdf_wd_ap@data, "all_wd.csv")
# write.csv(spdf_wn_ap@data, "all_wn.csv")
# write.csv(spdf_fd_ap@data, "all_fd.csv")
# write.csv(spdf_fn_ap@data, "all_fn.csv")
# write.csv(spdf_sd_ap@data, "all_sd.csv")
# write.csv(spdf_sn_ap@data, "all_sn.csv")

# 7.6. Write pres+abs points to Shapefiles ####
# to test and plot in ArcMap
# writeOGR(spdf_wd_ap, getwd(), "wd", driver = "ESRI Shapefile", overwrite_layer = F)
# writeOGR(spdf_wn_ap, getwd(), "wn", driver = "ESRI Shapefile", overwrite_layer = F)
# writeOGR(spdf_fd_ap, getwd(), "fd", driver = "ESRI Shapefile", overwrite_layer = F)
# writeOGR(spdf_fn_ap, getwd(), "fn", driver = "ESRI Shapefile", overwrite_layer = F)
# writeOGR(spdf_sd_ap, getwd(), "sd", driver = "ESRI Shapefile", overwrite_layer = F)
# writeOGR(spdf_sn_ap, getwd(), "sn", driver = "ESRI Shapefile", overwrite_layer = F)

# 7.8. Clean up ####
rm(spdf_wd, spdf_wd_abs, wd_abs_list, df_wd, wd_mcp90,
   spdf_wn, spdf_wn_abs, wn_abs_list, df_wn, wn_mcp90,
   spdf_fd, spdf_fd_abs, fd_abs_list, df_fd, fd_mcp90,
   spdf_fn, spdf_fn_abs, fn_abs_list, df_fn, fn_mcp90,
   spdf_sd, spdf_sd_abs, sd_abs_list, df_sd, sd_mcp90,
   spdf_sn, spdf_sn_abs, sn_abs_list, df_sn, sn_mcp90 )

#------------------------------------------------------------------------------#

# 8. Covariate layer prep ####
```

```
# 8.1. Load covariate layers into R ####
getwd()

# HAST LAYERS
habitat <- raster("habitat.tif")
tpi <- raster("tpi.tif")
slope <- raster("slope.tif")
road <- raster("road.tif")
dgrass100 <- raster("dgrass100.tif")
asrw <- raster("asrw.tif")
asrf <- raster("asrf.tif")
asrs <- raster("asrs.tif")
landsat <- raster("landsat.tif")

#import landsat
#landsat <- get_nlcd(asrs, landsat, year = 2011, dataset = "landcover") #downloaded to wd

#landsat <- raster("NLCD2011_LC_N36W081.tif")

# 8.2. Reconcile projections ####
# 8.2.1 Check proj4string for each layer ####
proj4string(habitat)
proj4string(tpi)
proj4string(slope)
proj4string(road)
proj4string(dgrass100)
proj4string(asrw)
proj4string(asrf)
proj4string(asrs)
proj4string(landsat)

# 8.2.2. Project rasters to match habitat layer ####
# slow process
tpi <- projectRaster(tpi, habitat, method = 'bilinear')
slope <- projectRaster(slope, habitat, method = 'bilinear')
road <- projectRaster(road, habitat, method = 'bilinear')
landsat <- projectRaster(landsat, habitat, method = 'bilinear')

# 8.2.3. Check proj4string for each layer ####
proj4string(habitat)
proj4string(tpi)
proj4string(slope)
proj4string(road)
proj4string(dgrass100)
proj4string(asrw)
proj4string(asrf)
```

```
proj4string(asrs)#all good!!
proj4string(landsat)

# 8.3. Clean up habitat layer ####

# 8.3.1. Convert habitat from numeric to factor ####
# slow process
habitat <- raster::ratify(habitat, count = TRUE)

# 8.3.2. Define levels in attribute table of habitat rasterlayer ####
levels(habitat)[[1]]
levels(habitat)[[1]]$landcover <- c('bare', 'grass', 'timber')

# 8.4. Crop all covariate rasters to same extent ####
habitat <- raster::crop(habitat, asrw)
tpi <- raster::crop(tpi, asrw)
slope <- raster::crop(slope, asrw)
road <- raster::crop(road, asrw)
dgrass100 <- raster::crop(dgrass100, asrw)
landsat <- raster::crop(landsat, asrw)

plot(landsat)

landsat <- raster::ratify(landsat, count = TRUE)

# 8.xx reclassify to habitats of interest #####
#build matrix
m <- c(0,11,0,11,24,24,24,31,31,31,41,41,41,42,42,
      42,43,43,43,52,52,52,71,71,71,Inf,0)
rclmat <- matrix(m, ncol=3, byrow = TRUE)
rclmat
landsat_reclass <- reclassify(landsat, rcl = rclmat)

landsat_reclass <- raster::ratify(landsat_reclass, count = TRUE)

levels(landsat_reclass)[[1]]
levels(landsat_reclass)[[1]]$type <- c('other','developed','barren','deciduous','evergreen',
                        'mixed','scrub','grass')
levels(landsat_reclass)[[1]]

# 8.5. Stack all rasters ####
#_o = original, unscaled values
rstack <- raster::stack(habitat,tpi,slope,road,dgrass100,asrw,asrf,asrs,landsat_reclass)
names(rstack)
names(rstack) <-
  c('habitat',
```

```
    'tpi_o',
    'slope_o',
    'road_o',
    'dgrass100_o',
    'asrw_o',
    'asrf_o',
    'asrs_o',
    'landsat_reclass')
names(rstack)
plot(rstack)
plot(landsat_reclass)

# 8.6. Pre-scaling mu & sigma ####
# Do not need to repeat this section across seasons

names(rstack)

# Means
rstack_mu_o <- rstack %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_o')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# SDs
rstack_sigma_o <- rstack %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_o')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

#check mean and sd
rstack_mu_o
rstack_sigma_o   #this issue somehow fixed itself when I moved to a new WD and updated
dplyr
# package... I was running an older version...

# Join
rstack_param_o <- rstack_mu_o %>%
  full_join(rstack_sigma_o, by = 'covariate')
```

```
# Result
rstack_param_o   #looks good - combined mu and sigma

# Clean up
rm(rstack_mu_o, rstack_sigma_o)

# 8.7. Plot ####
#plot(rstack)
# looks good

# 8.8. Clean up ####
rm(habitat, tpi, slope, road, dgrass100, asrw, asrf, asrs, landsat_reclass)


#------------------------------------------------------------------------------#
# Everything after this point must be repeated for each season/daynight combo.
#------------------------------------------------------------------------------#

#------------------------------------------------------------------------------#

# 9.  Winter Day  -- Point covariates prep ####

# 9.1. Extract covariate values to points ####

# Toggle season/daynight
toggle = 'wd'
if(toggle == 'wd'){ap = spdf_wd_ap}
if(toggle == 'wn'){ap = spdf_wn_ap}
if(toggle == 'fd'){ap = spdf_fd_ap}
if(toggle == 'fn'){ap = spdf_fn_ap}
if(toggle == 'sd'){ap = spdf_sd_ap}
if(toggle == 'sn'){ap = spdf_sn_ap}

# Extract from raster stack
head(ap)
ap@data[, names(rstack)] <- raster::extract(rstack,
                                    ap,
                                    method = 'simple')
head(ap)
str(ap@data)

# Rename ASR for this season
if(toggle %in% c('wd', 'wn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrw_o) %>%
```

```
    dplyr::select(-c(asrf_o, asrs_o))
}
if(toggle %in% c('fd', 'fn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrf_o) %>%
    dplyr::select(-c(asrw_o, asrs_o))
}
if(toggle %in% c('sd', 'sn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrs_o) %>%
    dplyr::select(-c(asrw_o, asrf_o))
}

head(ap)
# only 1 asr column now.
#still has all three asr columns- edit = add dplyr::select above - now it works


# 9.2. Scale & reflevel covariates of points ####

# _o  indicates original values of covariate
# _sc indicates scaled covariate

dat <- ap %>%

  # Demote from SpatialPointsDataFrame to data.frame
  as.data.frame() %>%

  # 9.2.1. Scale continuous covariates ####
mutate(tpi_sc = scale(tpi_o)) %>%
  mutate(slope_sc = scale(slope_o)) %>%
  mutate(road_sc = scale(road_o)) %>%
  mutate(dgrass100_sc = scale(dgrass100_o)) %>%
  mutate(asr_sc = scale(asr_o)) %>%

  # 9.2.2. Set reference level for habitat ####
mutate(habitat = factor(habitat,
                        levels = c(-63,1,6),
                        labels = c("bare", "grass", "timber"))) %>%
  mutate(habitat = relevel(habitat, ref = 'grass'))

head(dat)
str(dat)
table(dat$habitat)

# 9.3. Pre-scaling mean & SDs ####
```

```
mu_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_o <- mu_o %>%
  full_join(sigma_o, by = 'covariate')

# Result
params_o

# Clean up
rm(mu_o, sigma_o)

# 9.4. Post-scaling means & SDs ####
mu_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_sc <- mu_sc %>%
  full_join(sigma_sc, by = 'covariate')

# Result
```

```
# means should be about 0, and sd should be about 1 for all
params_sc

# Clean up
rm(mu_sc, sigma_sc)


#------------------------------------------------------------------------------#

# 10. - Scale covariate rasters ####

# 10.1. Subset raster stack to this season's layers ####
if(toggle %in% c('wd', 'wn')){asr_o = 'asrw_o'}
if(toggle %in% c('fd', 'fn')){asr_o = 'asrf_o'}
if(toggle %in% c('sd', 'sn')){asr_o = 'asrs_o'}

keep = c("habitat", "tpi_o", "slope_o", "road_o", "dgrass100_o","landsat_reclass")
rstack_season <- subset(rstack, subset = c(keep, asr_o))
names(rstack_season) <- c(keep, 'asr_o')

# 10.2. Scale continuous covariate rasters ####
# Scale all layers with names containing '_o'
# (omits 'habitat', leaving only continuous covariate layers)
params_o  # scaling parameters of points from section 9.3.
rstack_sc <- raster::scale(subset(rstack_season,
                                  subset = grep('_o',names(rstack_season)) ),
                           center = params_o$mu,
                           scale = params_o$sigma)

# Rename layers: replace _o with _sc
names(rstack_sc) <- gsub('_o', '_sc', names(rstack_sc))


# 10.3. Restack with habitat ####
rstack_sc <- raster::stack(raster::subset(rstack, subset='habitat'),
                           rstack_sc)

rstack_sc <- raster::stack(raster::subset(rstack, subset='landsat_reclass'),
                           rstack_sc)

# Result
rstack_sc
names(rstack_sc)
#plot(rstack_sc)

# 10.4. Post-scaling mu & sigma ####
```

```
# Means
rstack_mu_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# SDs
rstack_sigma_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# Join
rstack_param_sc <- rstack_mu_sc %>%
  full_join(rstack_sigma_sc, by = 'covariate')

# Result
rstack_param_sc

# Clean up
rm(rstack_mu_sc, rstack_sigma_sc)

# Compare
rstack_param_o      # pre-scaling mu & sigma
rstack_param_sc     # post-scaling mu & sigma for this season/daynight


#------------------------------------------------------------------------------#

# 11. Multicollinearity check ####

# 11.1 Input data ####
# Input data.frame from section 9.2.
head(dat)

# Format input data for analysis
glmerdat <- dat %>%
```

```
  dplyr::select(id = id,
                type = type,
                habitat = habitat,
                landsat_reclass = landsat_reclass,
                tpi = tpi_sc,
                slope = slope_sc,
                road = road_sc,
                dgrass100 = dgrass100_sc,
                asr = asr_sc)

str(glmerdat)

# change to factor and set ref level for landsat_reclass
levels(glmerdat$landsat_reclass)
glmerdat$landsat_reclass <- factor(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)                    <-                    c("other",
"developed","barren","deciduous","evergreen",
                              "mixed","scrub","grass")
glmerdat$landsat_reclass <- relevel(glmerdat$landsat_reclass, ref = "grass")
str(glmerdat)
head(glmerdat)

w = table(glmerdat$landsat_reclass)
w



# Strip attributes for compatibility with newdat in section 13: predict
attributes(glmerdat$tpi) <- NULL
attributes(glmerdat$slope) <- NULL
attributes(glmerdat$road) <- NULL
attributes(glmerdat$dgrass100) <- NULL
attributes(glmerdat$asr) <- NULL

str(glmerdat)
head(glmerdat)

# 11.2. Scatterplot matrix  ####

# Choose title
if(toggle == 'wd'){m = 'Winter Day'}
if(toggle == 'wn'){m = 'Winter Night'}
if(toggle == 'fd'){m = 'Fall Day'}
if(toggle == 'fn'){m = 'Fall Night'}
if(toggle == 'sd'){m = 'Summer Day'}
```

```
if(toggle == 'sn'){m = 'Summer Night'}


# Visual check for multicolinearity
psych::pairs.panels(
  glmerdat[, c("habitat","landsat_reclass","tpi", "slope", "road", "dgrass100", "asr")],
  method = "pearson",
  hist.col = "#00AFBB",
  density = TRUE,
  ellipses = TRUE,
  main = m
)

# 11.3. VIF - wd ####
vif(
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
)

#------------------------------------------------------------------------------#

# 12. Model Selection (AIC) ####

# 12.1. Base models ####

# 12.1.1. Null model ####
# Converges for Winter Day
options(na.action = "na.fail")
nullmod <- glmer(type ~ 1 + (1|id), data = glmerdat, family = 'binomial')
summary(nullmod)

# 12.1.2. Full model ####
# Converges for Winter Day
fullmod <-
  glmer(
    type ~ 1 + habitat +landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
summary(fullmod)

# 12.2. Dredge ####
dredge(fullmod, beta = "sd", evaluate = TRUE)
```

```
# 12.3. Top model ####
#adjust based on dredge output!!!
# Winter Day: type ~ 1 + habitat+ landsat_reclass + tpi + dgrass100 + (1|id)
refmod <-
  glmer(type ~ 1 + habitat +landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
        data = glmerdat,
        family = 'binomial')
summary(refmod)
#------------------------------------------------------------------------------#

# 13.  -- Predictions ####

# 13.1. Top model from Section 12 ####
# but without random effects
refmod.pred <-
  glm(type ~ habitat + tpi + slope + road + dgrass100 + asr,
      data = glmerdat,
      family = 'binomial')
summary(refmod.pred)
class(refmod.pred)


# 13.2. Prep input data fopr predictions ####

# Scaled rasters for predictions
rstack_sc
names(rstack_sc)

# raster layers to keep
if(toggle == 'wd'){ss = c('habitat', 'tpi_sc', 'dgrass100_sc')}

newdat <- rstack_sc %>%
  # subset to raster layers we want to keep
  raster::subset(subset = ss) %>%
  # convert to data.frame
  as.data.frame() %>%
  # format habitat as factor
  mutate(habitat = factor(habitat_landcover,
                          levels = c("bare", "grass", "timber") )) %>%
  mutate(habitat = relevel(habitat, ref = 'grass')) %>%
  dplyr::select(-c(habitat_COUNT, habitat_landcover)) %>%  #edit - added dplyr::select
here
  # remove _sc extensions on column names
  dplyr::rename_all(gsub, pattern = '*_sc$', replacement = '')
```

```
head(newdat)
str(newdat)


# 13.3. Predict - nonspatial ####
?predict.glm
newdat$pred.logit <- stats::predict(refmod.pred,
                            newdata = newdat,
                            level = 0)

head(newdat)
str(newdat)

# 13.4. Back-transform predicted values ####
library(boot)
?inv.logit
newdat$pred <- inv.logit(newdat$pred.logit)
head(newdat)

# 13.5. Promote predictions to spatial ####
pred.ras <- rstack_sc$habitat # template
pred.ras[] <- newdat$pred # fill in values
plot(pred.ras, main = m)

# 13.6. Plot with MCP & points ####
mcp = readOGR(dsn = getwd(),
          layer = paste0(toggle,'_mcp90'),
          stringsAsFactors = F)

plot(pred.ras, main = paste('Probability of elk & 90% MCP HR:', m) )
plot(mcp,border = 'black',add =T)
plot(ap[ap$type == 1,], add = T, pch = 20, cex = 0.01)

# 13.7. Save prediction raster to file ####
writeRaster(pred.ras, filename = paste0(toggle,'_pred.tif'))

# 9.  Winter Night  -- Point covariates prep ####

# 9.1. Extract covariate values to points ####

# Toggle season/daynight
toggle = 'wn'
if(toggle == 'wd'){ap = spdf_wd_ap}
if(toggle == 'wn'){ap = spdf_wn_ap}
if(toggle == 'fd'){ap = spdf_fd_ap}
if(toggle == 'fn'){ap = spdf_fn_ap}
```

```
if(toggle == 'sd'){ap = spdf_sd_ap}
if(toggle == 'sn'){ap = spdf_sn_ap}

# Extract from raster stack
head(ap)
ap@data[, names(rstack)] <- raster::extract(rstack,
                                    ap,
                                    method = 'simple')
head(ap)
str(ap@data)

# Rename ASR for this season
if(toggle %in% c('wd', 'wn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrw_o) %>%
    dplyr::select(-c(asrf_o, asrs_o))
}
if(toggle %in% c('fd', 'fn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrf_o) %>%
    dplyr::select(-c(asrw_o, asrs_o))
}
if(toggle %in% c('sd', 'sn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrs_o) %>%
    dplyr::select(-c(asrw_o, asrf_o))
}

head(ap)
# only 1 asr column now.
#still has all three asr columns- edit = add dplyr::select above - now it works


# 9.2. Scale & reflevel covariates of points ####

# _o  indicates original values of covariate
# _sc indicates scaled covariate

dat <- ap %>%

  # Demote from SpatialPointsDataFrame to data.frame
  as.data.frame() %>%

  # 9.2.1. Scale continuous covariates ####
mutate(tpi_sc = scale(tpi_o)) %>%
  mutate(slope_sc = scale(slope_o)) %>%
```

```
  mutate(road_sc = scale(road_o)) %>%
  mutate(dgrass100_sc = scale(dgrass100_o)) %>%
  mutate(asr_sc = scale(asr_o)) %>%

  # 9.2.2. Set reference level for habitat ####
mutate(habitat = factor(habitat,
                        levels = c(-63,1,6),
                        labels = c("bare", "grass", "timber"))) %>%
  mutate(habitat = relevel(habitat, ref = 'grass'))

head(dat)
str(dat)
table(dat$habitat)

# 9.3. Pre-scaling mean & SDs ####
mu_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_o <- mu_o %>%
  full_join(sigma_o, by = 'covariate')

# Result
params_o

# Clean up
rm(mu_o, sigma_o)

# 9.4. Post-scaling means & SDs ####
mu_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
```

```
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_sc <- mu_sc %>%
  full_join(sigma_sc, by = 'covariate')

# Result
# means should be about 0, and sd should be about 1 for all
params_sc

# Clean up
rm(mu_sc, sigma_sc)


#------------------------------------------------------------------------------#

# 10.- Scale covariate rasters ####

# 10.1. Subset raster stack to this season's layers ####
if(toggle %in% c('wd', 'wn')){asr_o = 'asrw_o'}
if(toggle %in% c('fd', 'fn')){asr_o = 'asrf_o'}
if(toggle %in% c('sd', 'sn')){asr_o = 'asrs_o'}

keep = c("habitat", "tpi_o", "slope_o", "road_o", "dgrass100_o","landsat_reclass")
rstack_season <- subset(rstack, subset = c(keep, asr_o))
names(rstack_season) <- c(keep, 'asr_o')

# 10.2. Scale continuous covariate rasters ####
# Scale all layers with names containing '_o'
# (omits 'habitat', leaving only continuous covariate layers)
params_o  # scaling parameters of points from section 9.3.
rstack_sc <- raster::scale(subset(rstack_season,
                                  subset = grep('_o',names(rstack_season)) ),
                           center = params_o$mu,
                           scale = params_o$sigma)

# Rename layers: replace _o with _sc
names(rstack_sc) <- gsub('_o', '_sc', names(rstack_sc))
```

```
# 10.3. Restack with habitat ####
rstack_sc <- raster::stack(raster::subset(rstack, subset='habitat'),
                           rstack_sc)

rstack_sc <- raster::stack(raster::subset(rstack, subset='landsat_reclass'),
                           rstack_sc)

# Result
rstack_sc
names(rstack_sc)
#plot(rstack_sc)

# 10.4. Post-scaling mu & sigma ####

# Means
rstack_mu_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# SDs
rstack_sigma_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# Join
rstack_param_sc <- rstack_mu_sc %>%
  full_join(rstack_sigma_sc, by = 'covariate')

# Result
rstack_param_sc

# Clean up
rm(rstack_mu_sc, rstack_sigma_sc)
```

```
# Compare
rstack_param_o      # pre-scaling mu & sigma
rstack_param_sc     # post-scaling mu & sigma for this season/daynight


#-------------------------------------------------------------------------#

# 11. Multicollinearity check ####

# 11.1 Input data ####
# Input data.frame from section 9.2.
head(dat)

# Format input data for analysis
glmerdat <- dat %>%
  dplyr::select(id = id,
                type = type,
                habitat = habitat,
                landsat_reclass = landsat_reclass,
                tpi = tpi_sc,
                slope = slope_sc,
                road = road_sc,
                dgrass100 = dgrass100_sc,
                asr = asr_sc)

str(glmerdat)

# change to factor and set ref level for landsat_reclass
levels(glmerdat$landsat_reclass)
glmerdat$landsat_reclass <- factor(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)                    <-                    c("other",
"developed","barren","deciduous","evergreen",
                              "mixed","scrub","grass")
glmerdat$landsat_reclass <- relevel(glmerdat$landsat_reclass, ref = "grass")
str(glmerdat)
head(glmerdat)

w = table(glmerdat$landsat_reclass)
w



# Strip attributes for compatibility with newdat in section 13: predict
attributes(glmerdat$tpi) <- NULL
attributes(glmerdat$slope) <- NULL
```

```
attributes(glmerdat$road) <- NULL
attributes(glmerdat$dgrass100) <- NULL
attributes(glmerdat$asr) <- NULL

str(glmerdat)
head(glmerdat)

# 11.2. Scatterplot matrix  ####

# Choose title
if(toggle == 'wd'){m = 'Winter Day'}
if(toggle == 'wn'){m = 'Winter Night'}
if(toggle == 'fd'){m = 'Fall Day'}
if(toggle == 'fn'){m = 'Fall Night'}
if(toggle == 'sd'){m = 'Summer Day'}
if(toggle == 'sn'){m = 'Summer Night'}


# Visual check for multicolinearity
psych::pairs.panels(
  glmerdat[, c("habitat","landsat_reclass","tpi", "slope", "road", "dgrass100", "asr")],
  method = "pearson",
  hist.col = "#00AFBB",
  density = TRUE,
  ellipses = TRUE,
  main = m
)

# 11.3. VIF - wd ####
vif(
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
)

#------------------------------------------------------------------------#

# 12. Model Selection (AIC) ####

# 12.1. Base models ####

# 12.1.1. Null model ####

options(na.action = "na.fail")
```

```
nullmod <- glmer(type ~ 1 + (1|id), data = glmerdat, family = 'binomial')
summary(nullmod)

# 12.1.2. Full model ####

fullmod <-
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
summary(fullmod)

# 12.2. Dredge ####
dredge(fullmod, beta = "sd", evaluate = TRUE)

# 12.3. Top model ####
#adjust based on dredge output!!!

refmod <-
  glmer(type ~ 1 + habitat +landsat_reclass + tpi + dgrass100 + slope + (1|id),
        data = glmerdat,
        family = 'binomial')
summary(refmod)
#------------------------------------------------------------------------------#

# 13. -- Predictions ####

# 13.1. Top model from Section 12 ####
# but without random effects
refmod.pred <-
  glm(type ~ habitat + tpi + dgrass100 + slope,
      data = glmerdat,
      family = 'binomial')
summary(refmod.pred)
class(refmod.pred)


# 13.2. Prep input data fopr predictions ####

# Scaled rasters for predictions
rstack_sc
names(rstack_sc)

# raster layers to keep
if(toggle == 'wd'){ss = c('habitat', 'tpi_sc', 'dgrass100_sc')}
```

```
newdat <- rstack_sc %>%
  # subset to raster layers we want to keep
  raster::subset(subset = ss) %>%
  # convert to data.frame
  as.data.frame() %>%
  # format habitat as factor
  mutate(habitat = factor(habitat_landcover,
                          levels = c("bare", "grass", "timber") )) %>%
  mutate(habitat = relevel(habitat, ref = 'grass')) %>%
  dplyr::select(-c(habitat_COUNT, habitat_landcover)) %>%  #edit - added dplyr::select
here
  # remove _sc extensions on column names
  dplyr::rename_all(gsub, pattern = '*_sc$', replacement = '')

head(newdat)
str(newdat)


# 13.3. Predict - nonspatial ####
?predict.glm
newdat$pred.logit <- stats::predict(refmod.pred,
                                    newdata = newdat,
                                    level = 0)

head(newdat)
str(newdat)

# 13.4. Back-transform predicted values ####
library(boot)
?inv.logit
newdat$pred <- inv.logit(newdat$pred.logit)
head(newdat)

# 13.5. Promote predictions to spatial ####
pred.ras <- rstack_sc$habitat # template
pred.ras[] <- newdat$pred # fill in values
plot(pred.ras, main = m)

# 13.6. Plot with MCP & points ####
mcp = readOGR(dsn = getwd(),
              layer = paste0(toggle,'_mcp90'),
              stringsAsFactors = F)

plot(pred.ras, main = paste('Probability of elk & 90% MCP HR:', m) )
plot(mcp,border = 'black',add =T)
```

```
plot(ap[ap$type == 1,], add = T, pch = 20, cex = 0.01)

# 13.7. Save prediction raster to file ####
writeRaster(pred.ras, filename = paste0(toggle,'_pred.tif'))

# 9.  Fall Day   -- Point covariates prep ####

# 9.1. Extract covariate values to points ####

# Toggle season/daynight
toggle = 'fd'
if(toggle == 'wd'){ap = spdf_wd_ap}
if(toggle == 'wn'){ap = spdf_wn_ap}
if(toggle == 'fd'){ap = spdf_fd_ap}
if(toggle == 'fn'){ap = spdf_fn_ap}
if(toggle == 'sd'){ap = spdf_sd_ap}
if(toggle == 'sn'){ap = spdf_sn_ap}

# Extract from raster stack
head(ap)
ap@data[, names(rstack)] <- raster::extract(rstack,
                                    ap,
                                    method = 'simple')
head(ap)
str(ap@data)

# Rename ASR for this season
if(toggle %in% c('wd', 'wn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrw_o) %>%
    dplyr::select(-c(asrf_o, asrs_o))
}
if(toggle %in% c('fd', 'fn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrf_o) %>%
    dplyr::select(-c(asrw_o, asrs_o))
}
if(toggle %in% c('sd', 'sn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrs_o) %>%
    dplyr::select(-c(asrw_o, asrf_o))
}

head(ap)
# only 1 asr column now.
#still has all three asr columns- edit = add dplyr::select above - now it works
```

```
# 9.2. Scale & reflevel covariates of points ####

# _o  indicates original values of covariate
# _sc indicates scaled covariate

dat <- ap %>%

  # Demote from SpatialPointsDataFrame to data.frame
  as.data.frame() %>%

  # 9.2.1. Scale continuous covariates ####
mutate(tpi_sc = scale(tpi_o)) %>%
  mutate(slope_sc = scale(slope_o)) %>%
  mutate(road_sc = scale(road_o)) %>%
  mutate(dgrass100_sc = scale(dgrass100_o)) %>%
  mutate(asr_sc = scale(asr_o)) %>%

  # 9.2.2. Set reference level for habitat ####
mutate(habitat = factor(habitat,
                        levels = c(-63,1,6),
                        labels = c("bare", "grass", "timber"))) %>%
  mutate(habitat = relevel(habitat, ref = 'grass'))

head(dat)
str(dat)
table(dat$habitat)

# 9.3. Pre-scaling mean & SDs ####
mu_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')
```

```
params_o <- mu_o %>%
  full_join(sigma_o, by = 'covariate')

# Result
params_o

# Clean up
rm(mu_o, sigma_o)

# 9.4. Post-scaling means & SDs ####
mu_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_sc <- mu_sc %>%
  full_join(sigma_sc, by = 'covariate')

# Result
# means should be about 0, and sd should be about 1 for all
params_sc

# Clean up
rm(mu_sc, sigma_sc)


#------------------------------------------------------------------------------#

# 10. - Scale covariate rasters ####

# 10.1. Subset raster stack to this season's layers ####
if(toggle %in% c('wd', 'wn')){asr_o = 'asrw_o'}
if(toggle %in% c('fd', 'fn')){asr_o = 'asrf_o'}
if(toggle %in% c('sd', 'sn')){asr_o = 'asrs_o'}
```

```
keep = c("habitat", "tpi_o", "slope_o", "road_o", "dgrass100_o","landsat_reclass")
rstack_season <- subset(rstack, subset = c(keep, asr_o))
names(rstack_season) <- c(keep, 'asr_o')

# 10.2. Scale continuous covariate rasters ####
# Scale all layers with names containing '_o'
# (omits 'habitat', leaving only continuous covariate layers)
params_o  # scaling parameters of points from section 9.3.
rstack_sc <- raster::scale(subset(rstack_season,
                                  subset = grep('_o',names(rstack_season)) ),
                           center = params_o$mu,
                           scale = params_o$sigma)

# Rename layers: replace _o with _sc
names(rstack_sc) <- gsub('_o', '_sc', names(rstack_sc))


# 10.3. Restack with habitat ####
rstack_sc <- raster::stack(raster::subset(rstack, subset='habitat'),
                           rstack_sc)

rstack_sc <- raster::stack(raster::subset(rstack, subset='landsat_reclass'),
                           rstack_sc)

# Result
rstack_sc
names(rstack_sc)
#plot(rstack_sc)

# 10.4. Post-scaling mu & sigma ####

# Means
rstack_mu_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# SDs
rstack_sigma_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
```

```
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# Join
rstack_param_sc <- rstack_mu_sc %>%
  full_join(rstack_sigma_sc, by = 'covariate')

# Result
rstack_param_sc

# Clean up
rm(rstack_mu_sc, rstack_sigma_sc)

# Compare
rstack_param_o      # pre-scaling mu & sigma
rstack_param_sc     # post-scaling mu & sigma for this season/daynight


#-------------------------------------------------------------------------------#

# 11. Multicollinearity check ####

# 11.1 Input data ####
# Input data.frame from section 9.2.
head(dat)

# Format input data for analysis
glmerdat <- dat %>%
  dplyr::select(id = id,
                type = type,
                habitat = habitat,
                landsat_reclass = landsat_reclass,
                tpi = tpi_sc,
                slope = slope_sc,
                road = road_sc,
                dgrass100 = dgrass100_sc,
                asr = asr_sc)

str(glmerdat)

# change to factor and set ref level for landsat_reclass
levels(glmerdat$landsat_reclass)
glmerdat$landsat_reclass <- factor(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)
```

```
levels(glmerdat$landsat_reclass) <- c("other",
"developed","barren","deciduous","evergreen",
                                      "mixed","scrub","grass")
glmerdat$landsat_reclass <- relevel(glmerdat$landsat_reclass, ref = "grass")
str(glmerdat)
head(glmerdat)

w = table(glmerdat$landsat_reclass)
w



# Strip attributes for compatibility with newdat in section 13: predict
attributes(glmerdat$tpi) <- NULL
attributes(glmerdat$slope) <- NULL
attributes(glmerdat$road) <- NULL
attributes(glmerdat$dgrass100) <- NULL
attributes(glmerdat$asr) <- NULL

str(glmerdat)
head(glmerdat)

# 11.2. Scatterplot matrix  ####

# Choose title
if(toggle == 'wd'){m = 'Winter Day'}
if(toggle == 'wn'){m = 'Winter Night'}
if(toggle == 'fd'){m = 'Fall Day'}
if(toggle == 'fn'){m = 'Fall Night'}
if(toggle == 'sd'){m = 'Summer Day'}
if(toggle == 'sn'){m = 'Summer Night'}


# Visual check for multicolinearity
psych::pairs.panels(
  glmerdat[, c("habitat","landsat_reclass","tpi", "slope", "road", "dgrass100", "asr")],
  method = "pearson",
  hist.col = "#00AFBB",
  density = TRUE,
  ellipses = TRUE,
  main = m
)

# 11.3. VIF - wd ####
vif(
  glmer(
```

```
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
)

#------------------------------------------------------------------------------#

# 12. Model Selection (AIC) ####

# 12.1. Base models ####

# 12.1.1. Null model ####

options(na.action = "na.fail")
nullmod <- glmer(type ~ 1 + (1|id), data = glmerdat, family = 'binomial')
summary(nullmod)

# 12.1.2. Full model ####

fullmod <-
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
summary(fullmod)

# 12.2. Dredge ####
dredge(fullmod, beta = "sd", evaluate = TRUE)

# 12.3. Top model ####
#adjust based on dredge output!!!

refmod <-
  glmer( type ~ 1 + habitat + landsat_reclass + tpi + slope + dgrass100 + asr + (1|id),
         data = glmerdat,
         family = 'binomial')
summary(refmod)
#------------------------------------------------------------------------------#

# 13.  -- Predictions ####

# 13.1. Top model from Section 12 ####
# but without random effects
refmod.pred <-
```

```
  glm(type ~ habitat + landsat_reclass + tpi + slope + dgrass100 + asr,
      data = glmerdat,
      family = 'binomial')
summary(refmod.pred)
class(refmod.pred)


# 13.2. Prep input data fopr predictions ####

# Scaled rasters for predictions
rstack_sc
names(rstack_sc)

# raster layers to keep
if(toggle == 'wd'){ss = c('habitat', 'tpi_sc', 'dgrass100_sc')}

newdat <- rstack_sc %>%
  # subset to raster layers we want to keep
  raster::subset(subset = ss) %>%
  # convert to data.frame
  as.data.frame() %>%
  # format habitat as factor
  mutate(habitat = factor(habitat_landcover,
                          levels = c("bare", "grass", "timber") )) %>%
  mutate(habitat = relevel(habitat, ref = 'grass')) %>%
  dplyr::select(-c(habitat_COUNT, habitat_landcover)) %>%  #edit - added dplyr::select
here
  # remove _sc extensions on column names
  dplyr::rename_all(gsub, pattern = '*_sc$', replacement = '')

head(newdat)
str(newdat)


# 13.3. Predict - nonspatial ####
?predict.glm
newdat$pred.logit <- stats::predict(refmod.pred,
                                    newdata = newdat,
                                    level = 0)

head(newdat)
str(newdat)

# 13.4. Back-transform predicted values ####
library(boot)
?inv.logit
```

```
newdat$pred <- inv.logit(newdat$pred.logit)
head(newdat)

# 13.5. Promote predictions to spatial ####
pred.ras <- rstack_sc$habitat # template
pred.ras[] <- newdat$pred # fill in values
plot(pred.ras, main = m)

# 13.6. Plot with MCP & points ####
mcp = readOGR(dsn = getwd(),
              layer = paste0(toggle,'_mcp90'),
              stringsAsFactors = F)

plot(pred.ras, main = paste('Probability of elk & 90% MCP HR:', m) )
plot(mcp,border = 'black',add =T)
plot(ap[ap$type == 1,], add = T, pch = 20, cex = 0.01)

# 13.7. Save prediction raster to file ####
writeRaster(pred.ras, filename = paste0(toggle,'_pred.tif'))

# 9.  Fall Night  -- Point covariates prep ####

# 9.1. Extract covariate values to points ####

# Toggle season/daynight
toggle = 'fn'
if(toggle == 'wd'){ap = spdf_wd_ap}
if(toggle == 'wn'){ap = spdf_wn_ap}
if(toggle == 'fd'){ap = spdf_fd_ap}
if(toggle == 'fn'){ap = spdf_fn_ap}
if(toggle == 'sd'){ap = spdf_sd_ap}
if(toggle == 'sn'){ap = spdf_sn_ap}

# Extract from raster stack
head(ap)
ap@data[, names(rstack)] <- raster::extract(rstack,
                                            ap,
                                            method = 'simple')
head(ap)
str(ap@data)

# Rename ASR for this season
if(toggle %in% c('wd', 'wn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrw_o) %>%
    dplyr::select(-c(asrf_o, asrs_o))
```

```
}
if(toggle %in% c('fd', 'fn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrf_o) %>%
    dplyr::select(-c(asrw_o, asrs_o))
}
if(toggle %in% c('sd', 'sn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrs_o) %>%
    dplyr::select(-c(asrw_o, asrf_o))
}

head(ap)
# only 1 asr column now.
#still has all three asr columns- edit = add dplyr::select above - now it works


# 9.2. Scale & reflevel covariates of points ####

# _o  indicates original values of covariate
# _sc indicates scaled covariate

dat <- ap %>%

  # Demote from SpatialPointsDataFrame to data.frame
  as.data.frame() %>%

  # 9.2.1. Scale continuous covariates ####
mutate(tpi_sc = scale(tpi_o)) %>%
  mutate(slope_sc = scale(slope_o)) %>%
  mutate(road_sc = scale(road_o)) %>%
  mutate(dgrass100_sc = scale(dgrass100_o)) %>%
  mutate(asr_sc = scale(asr_o)) %>%

  # 9.2.2. Set reference level for habitat ####
mutate(habitat = factor(habitat,
                        levels = c(-63,1,6),
                        labels = c("bare", "grass", "timber"))) %>%
  mutate(habitat = relevel(habitat, ref = 'grass'))

head(dat)
str(dat)
table(dat$habitat)

# 9.3. Pre-scaling mean & SDs ####
mu_o <- dat %>%
```

```
  dplyr::summarise_at(vars(contains('_o')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_o <- mu_o %>%
  full_join(sigma_o, by = 'covariate')

# Result
params_o

# Clean up
rm(mu_o, sigma_o)

# 9.4. Post-scaling means & SDs ####
mu_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_sc <- mu_sc %>%
  full_join(sigma_sc, by = 'covariate')

# Result
# means should be about 0, and sd should be about 1 for all
```

```
params_sc

# Clean up
rm(mu_sc, sigma_sc)


#------------------------------------------------------------------------------#

# 10.  - Scale covariate rasters ####

# 10.1. Subset raster stack to this season's layers ####
if(toggle %in% c('wd', 'wn')){asr_o = 'asrw_o'}
if(toggle %in% c('fd', 'fn')){asr_o = 'asrf_o'}
if(toggle %in% c('sd', 'sn')){asr_o = 'asrs_o'}

keep = c("habitat", "tpi_o", "slope_o", "road_o", "dgrass100_o","landsat_reclass")
rstack_season <- subset(rstack, subset = c(keep, asr_o))
names(rstack_season) <- c(keep, 'asr_o')

# 10.2. Scale continuous covariate rasters ####
# Scale all layers with names containing '_o'
# (omits 'habitat', leaving only continuous covariate layers)
params_o  # scaling parameters of points from section 9.3.
rstack_sc <- raster::scale(subset(rstack_season,
                                  subset = grep('_o',names(rstack_season)) ),
                           center = params_o$mu,
                           scale = params_o$sigma)

# Rename layers: replace _o with _sc
names(rstack_sc) <- gsub('_o', '_sc', names(rstack_sc))


# 10.3. Restack with habitat ####
rstack_sc <- raster::stack(raster::subset(rstack, subset='habitat'),
                           rstack_sc)

rstack_sc <- raster::stack(raster::subset(rstack, subset='landsat_reclass'),
                           rstack_sc)

# Result
rstack_sc
names(rstack_sc)
#plot(rstack_sc)

# 10.4. Post-scaling mu & sigma ####
```

```
# Means
rstack_mu_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# SDs
rstack_sigma_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# Join
rstack_param_sc <- rstack_mu_sc %>%
  full_join(rstack_sigma_sc, by = 'covariate')

# Result
rstack_param_sc

# Clean up
rm(rstack_mu_sc, rstack_sigma_sc)

# Compare
rstack_param_o      # pre-scaling mu & sigma
rstack_param_sc     # post-scaling mu & sigma for this season/daynight


#------------------------------------------------------------------------------#

# 11. Multicollinearity check ####

# 11.1 Input data ####
# Input data.frame from section 9.2.
head(dat)

# Format input data for analysis
glmerdat <- dat %>%
  dplyr::select(id = id,
```

```
            type = type,
            habitat = habitat,
            landsat_reclass = landsat_reclass,
            tpi = tpi_sc,
            slope = slope_sc,
            road = road_sc,
            dgrass100 = dgrass100_sc,
            asr = asr_sc)

str(glmerdat)

# change to factor and set ref level for landsat_reclass
levels(glmerdat$landsat_reclass)
glmerdat$landsat_reclass <- factor(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)                    <-                    c("other",
"developed","barren","deciduous","evergreen",
                        "mixed","scrub","grass")
glmerdat$landsat_reclass <- relevel(glmerdat$landsat_reclass, ref = "grass")
str(glmerdat)
head(glmerdat)

w = table(glmerdat$landsat_reclass)
w



# Strip attributes for compatibility with newdat in section 13: predict
attributes(glmerdat$tpi) <- NULL
attributes(glmerdat$slope) <- NULL
attributes(glmerdat$road) <- NULL
attributes(glmerdat$dgrass100) <- NULL
attributes(glmerdat$asr) <- NULL

str(glmerdat)
head(glmerdat)

# 11.2. Scatterplot matrix  ####

# Choose title
if(toggle == 'wd'){m = 'Winter Day'}
if(toggle == 'wn'){m = 'Winter Night'}
if(toggle == 'fd'){m = 'Fall Day'}
if(toggle == 'fn'){m = 'Fall Night'}
if(toggle == 'sd'){m = 'Summer Day'}
if(toggle == 'sn'){m = 'Summer Night'}
```

```
# Visual check for multicolinearity
psych::pairs.panels(
  glmerdat[, c("habitat","landsat_reclass","tpi", "slope", "road", "dgrass100", "asr")],
  method = "pearson",
  hist.col = "#00AFBB",
  density = TRUE,
  ellipses = TRUE,
  main = m
)

# 11.3. VIF - wd ####
vif(
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
)

#------------------------------------------------------------------------#

# 12. Model Selection (AIC) ####

# 12.1. Base models ####

# 12.1.1. Null model ####

options(na.action = "na.fail")
nullmod <- glmer(type ~ 1 + (1|id), data = glmerdat, family = 'binomial')
summary(nullmod)

# 12.1.2. Full model ####

fullmod <-
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
summary(fullmod)

# 12.2. Dredge ####
dredge(fullmod, beta = "sd", evaluate = TRUE)
```

```
# 12.3. Top model ####
#adjust based on dredge output!!!

refmod <-
  glmer(type ~ 1 + habitat + landsat_reclass + tpi + slope + dgrass100 + asr + (1|id),
        data = glmerdat,
        family = 'binomial')
summary(refmod)
#------------------------------------------------------------------------------#

# 13. -- Predictions ####

# 13.1. Top model from Section 12 ####
# but without random effects
refmod.pred <-
  glm(type ~ habitat + tpi + slope + dgrass100 + asr,
      data = glmerdat,
      family = 'binomial')
summary(refmod.pred)
class(refmod.pred)


# 13.2. Prep input data fopr predictions ####

# Scaled rasters for predictions
rstack_sc
names(rstack_sc)

# raster layers to keep
if(toggle == 'wd'){ss = c('habitat', 'tpi_sc', 'dgrass100_sc')}

newdat <- rstack_sc %>%
  # subset to raster layers we want to keep
  raster::subset(subset = ss) %>%
  # convert to data.frame
  as.data.frame() %>%
  # format habitat as factor
  mutate(habitat = factor(habitat_landcover,
                          levels = c("bare", "grass", "timber") )) %>%
  mutate(habitat = relevel(habitat, ref = 'grass')) %>%
  dplyr::select(-c(habitat_COUNT, habitat_landcover)) %>%  #edit - added dplyr::select
here
  # remove _sc extensions on column names
  dplyr::rename_all(gsub, pattern = '*_sc$', replacement = '')

head(newdat)
```

```
str(newdat)


# 13.3. Predict - nonspatial ####
?predict.glm
newdat$pred.logit <- stats::predict(refmod.pred,
                            newdata = newdat,
                            level = 0)

head(newdat)
str(newdat)

# 13.4. Back-transform predicted values ####
library(boot)
?inv.logit
newdat$pred <- inv.logit(newdat$pred.logit)
head(newdat)

# 13.5. Promote predictions to spatial ####
pred.ras <- rstack_sc$habitat # template
pred.ras[] <- newdat$pred # fill in values
plot(pred.ras, main = m)

# 13.6. Plot with MCP & points ####
mcp = readOGR(dsn = getwd(),
            layer = paste0(toggle,'_mcp90'),
            stringsAsFactors = F)

plot(pred.ras, main = paste('Probability of elk & 90% MCP HR:', m) )
plot(mcp,border = 'black',add =T)
plot(ap[ap$type == 1,], add = T, pch = 20, cex = 0.01)

# 13.7. Save prediction raster to file ####
writeRaster(pred.ras, filename = paste0(toggle,'_pred.tif'))

#-------------------------------------------------------------------------#

# 9.  Summer Day  Point covariates prep ####

# 9.1. Extract covariate values to points ####

# Toggle season/daynight
toggle = 'sd'
if(toggle == 'wd'){ap = spdf_wd_ap}
if(toggle == 'wn'){ap = spdf_wn_ap}
if(toggle == 'fd'){ap = spdf_fd_ap}
```

```
if(toggle == 'fn'){ap = spdf_fn_ap}
if(toggle == 'sd'){ap = spdf_sd_ap}
if(toggle == 'sn'){ap = spdf_sn_ap}

# Extract from raster stack
head(ap)
ap@data[, names(rstack)] <- raster::extract(rstack,
                                    ap,
                                    method = 'simple')
head(ap)
str(ap@data)

# Rename ASR for this season
if(toggle %in% c('wd', 'wn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrw_o) %>%
    dplyr::select(-c(asrf_o, asrs_o))
}
if(toggle %in% c('fd', 'fn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrf_o) %>%
    dplyr::select(-c(asrw_o, asrs_o))
}
if(toggle %in% c('sd', 'sn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrs_o) %>%
    dplyr::select(-c(asrw_o, asrf_o))
}

head(ap)
# only 1 asr column now.
#still has all three asr columns- edit = add dplyr::select above - now it works


# 9.2. Scale & reflevel covariates of points ####

# _o  indicates original values of covariate
# _sc indicates scaled covariate

dat <- ap %>%

  # Demote from SpatialPointsDataFrame to data.frame
  as.data.frame() %>%

  # 9.2.1. Scale continuous covariates ####
mutate(tpi_sc = scale(tpi_o)) %>%
```

```
  mutate(slope_sc = scale(slope_o)) %>%
  mutate(road_sc = scale(road_o)) %>%
  mutate(dgrass100_sc = scale(dgrass100_o)) %>%
  mutate(asr_sc = scale(asr_o)) %>%

  # 9.2.2. Set reference level for habitat ####
mutate(habitat = factor(habitat,
                        levels = c(-63,1,6),
                        labels = c("bare", "grass", "timber"))) %>%
  mutate(habitat = relevel(habitat, ref = 'grass'))

head(dat)
str(dat)
table(dat$habitat)

# 9.3. Pre-scaling mean & SDs ####
mu_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_o <- mu_o %>%
  full_join(sigma_o, by = 'covariate')

# Result
params_o

# Clean up
rm(mu_o, sigma_o)

# 9.4. Post-scaling means & SDs ####
mu_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
```

```
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_sc <- mu_sc %>%
  full_join(sigma_sc, by = 'covariate')

# Result
# means should be about 0, and sd should be about 1 for all
params_sc

# Clean up
rm(mu_sc, sigma_sc)


#------------------------------------------------------------------------------#

# 10. - Scale covariate rasters ####

# 10.1. Subset raster stack to this season's layers ####
if(toggle %in% c('wd', 'wn')){asr_o = 'asrw_o'}
if(toggle %in% c('fd', 'fn')){asr_o = 'asrf_o'}
if(toggle %in% c('sd', 'sn')){asr_o = 'asrs_o'}

keep = c("habitat", "tpi_o", "slope_o", "road_o", "dgrass100_o","landsat_reclass")
rstack_season <- subset(rstack, subset = c(keep, asr_o))
names(rstack_season) <- c(keep, 'asr_o')

# 10.2. Scale continuous covariate rasters ####
# Scale all layers with names containing '_o'
# (omits 'habitat', leaving only continuous covariate layers)
params_o  # scaling parameters of points from section 9.3.
rstack_sc <- raster::scale(subset(rstack_season,
                                  subset = grep('_o',names(rstack_season)) ),
                           center = params_o$mu,
                           scale = params_o$sigma)

# Rename layers: replace _o with _sc
```

```
names(rstack_sc) <- gsub('_o', '_sc', names(rstack_sc))


# 10.3. Restack with habitat ####
rstack_sc <- raster::stack(raster::subset(rstack, subset='habitat'),
                           rstack_sc)

rstack_sc <- raster::stack(raster::subset(rstack, subset='landsat_reclass'),
                           rstack_sc)

# Result
rstack_sc
names(rstack_sc)
#plot(rstack_sc)

# 10.4. Post-scaling mu & sigma ####

# Means
rstack_mu_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# SDs
rstack_sigma_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# Join
rstack_param_sc <- rstack_mu_sc %>%
  full_join(rstack_sigma_sc, by = 'covariate')

# Result
rstack_param_sc

# Clean up
rm(rstack_mu_sc, rstack_sigma_sc)
```

```
# Compare
rstack_param_o      # pre-scaling mu & sigma
rstack_param_sc     # post-scaling mu & sigma for this season/daynight


#-------------------------------------------------------------------------------#

# 11. Multicollinearity check ####

# 11.1 Input data ####
# Input data.frame from section 9.2.
head(dat)

# Format input data for analysis
glmerdat <- dat %>%
  dplyr::select(id = id,
                type = type,
                habitat = habitat,
                landsat_reclass = landsat_reclass,
                tpi = tpi_sc,
                slope = slope_sc,
                road = road_sc,
                dgrass100 = dgrass100_sc,
                asr = asr_sc)

str(glmerdat)

# change to factor and set ref level for landsat_reclass
levels(glmerdat$landsat_reclass)
glmerdat$landsat_reclass <- factor(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass)                                                    <-
c("other","developed","barren","deciduous","evergreen",
                              "mixed","scrub","grass")
glmerdat$landsat_reclass <- relevel(glmerdat$landsat_reclass, ref = "grass")
str(glmerdat)
head(glmerdat)

w = table(glmerdat$landsat_reclass)
w



# Strip attributes for compatibility with newdat in section 13: predict
attributes(glmerdat$tpi) <- NULL
```

```
attributes(glmerdat$slope) <- NULL
attributes(glmerdat$road) <- NULL
attributes(glmerdat$dgrass100) <- NULL
attributes(glmerdat$asr) <- NULL

str(glmerdat)
head(glmerdat)

# 11.2. Scatterplot matrix  ####

# Choose title
if(toggle == 'wd'){m = 'Winter Day'}
if(toggle == 'wn'){m = 'Winter Night'}
if(toggle == 'fd'){m = 'Fall Day'}
if(toggle == 'fn'){m = 'Fall Night'}
if(toggle == 'sd'){m = 'Summer Day'}
if(toggle == 'sn'){m = 'Summer Night'}


# Visual check for multicolinearity
psych::pairs.panels(
  glmerdat[, c("habitat","landsat_reclass","tpi", "slope", "road", "dgrass100", "asr")],
  method = "pearson",
  hist.col = "#00AFBB",
  density = TRUE,
  ellipses = TRUE,
  main = m
)

# 11.3. VIF - wd ####
vif(
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
)

#-------------------------------------------------------------------------------#

# 12. Model Selection (AIC) ####

# 12.1. Base models ####

# 12.1.1. Null model ####
```

```
options(na.action = "na.fail")
nullmod <- glmer(type ~ 1 + (1|id), data = glmerdat, family = 'binomial')
summary(nullmod)

# 12.1.2. Full model ####

fullmod <-
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
summary(fullmod)

# 12.2. Dredge ####
dredge(fullmod, beta = "sd", evaluate = TRUE)

# 12.3. Top model ####
#adjust based on dredge output!!!

refmod <-
  glmer(type ~ 1 + habitat + landsat_reclass + tpi + road + dgrass100 + asr + (1|id),
        data = glmerdat,
        family = 'binomial')
summary(refmod)
#------------------------------------------------------------------------------#

# 13.  -- Predictions ####

# 13.1. Top model from Section 12 ####
# but without random effects
refmod.pred <-
  glm(type ~ habitat + landsat_reclass + tpi + road + dgrass100 + asr,
      data = glmerdat,
      family = 'binomial')
summary(refmod.pred)
class(refmod.pred)


# 13.2. Prep input data fopr predictions ####

# Scaled rasters for predictions
rstack_sc
names(rstack_sc)

# raster layers to keep
```

```
if(toggle == 'wd'){ss = c('habitat', 'tpi_sc', 'dgrass100_sc')}

newdat <- rstack_sc %>%
  # subset to raster layers we want to keep
  raster::subset(subset = ss) %>%
  # convert to data.frame
  as.data.frame() %>%
  # format habitat as factor
  mutate(habitat = factor(habitat_landcover,
                          levels = c("bare", "grass", "timber") )) %>%
  mutate(habitat = relevel(habitat, ref = 'grass')) %>%
  dplyr::select(-c(habitat_COUNT, habitat_landcover)) %>%  #edit - added dplyr::select
here
  # remove _sc extensions on column names
  dplyr::rename_all(gsub, pattern = '*_sc$', replacement = '')

head(newdat)
str(newdat)


# 13.3. Predict - nonspatial ####
?predict.glm
newdat$pred.logit <- stats::predict(refmod.pred,
                                    newdata = newdat,
                                    level = 0)

head(newdat)
str(newdat)

# 13.4. Back-transform predicted values ####
library(boot)
?inv.logit
newdat$pred <- inv.logit(newdat$pred.logit)
head(newdat)

# 13.5. Promote predictions to spatial ####
pred.ras <- rstack_sc$habitat # template
pred.ras[] <- newdat$pred # fill in values
plot(pred.ras, main = m)

# 13.6. Plot with MCP & points ####
mcp = readOGR(dsn = getwd(),
              layer = paste0(toggle,'_mcp90'),
              stringsAsFactors = F)

plot(pred.ras, main = paste('Probability of elk & 90% MCP HR:', m) )
```

```
plot(mcp,border = 'black',add =T)
plot(ap[ap$type == 1,], add = T, pch = 20, cex = 0.01)

# 13.7. Save prediction raster to file ####
writeRaster(pred.ras, filename = paste0(toggle,'_pred.tif'))

# 9.  Summer Night -- Point covariates prep ####

# 9.1. Extract covariate values to points ####

# Toggle season/daynight
toggle = 'sn'
if(toggle == 'wd'){ap = spdf_wd_ap}
if(toggle == 'wn'){ap = spdf_wn_ap}
if(toggle == 'fd'){ap = spdf_fd_ap}
if(toggle == 'fn'){ap = spdf_fn_ap}
if(toggle == 'sd'){ap = spdf_sd_ap}
if(toggle == 'sn'){ap = spdf_sn_ap}

# Extract from raster stack
head(ap)
ap@data[, names(rstack)] <- raster::extract(rstack,
                                    ap,
                                    method = 'simple')
head(ap)
str(ap@data)

# Rename ASR for this season
if(toggle %in% c('wd', 'wn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrw_o) %>%
    dplyr::select(-c(asrf_o, asrs_o))
}
if(toggle %in% c('fd', 'fn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrf_o) %>%
    dplyr::select(-c(asrw_o, asrs_o))
}
if(toggle %in% c('sd', 'sn')){
  ap@data <- ap@data %>%
    dplyr::rename(asr_o = asrs_o) %>%
    dplyr::select(-c(asrw_o, asrf_o))
}

head(ap)
# only 1 asr column now.
```

```
#still has all three asr columns- edit = add dplyr::select above - now it works


# 9.2. Scale & reflevel covariates of points ####

# _o  indicates original values of covariate
# _sc indicates scaled covariate

dat <- ap %>%

  # Demote from SpatialPointsDataFrame to data.frame
  as.data.frame() %>%

  # 9.2.1. Scale continuous covariates ####
mutate(tpi_sc = scale(tpi_o)) %>%
  mutate(slope_sc = scale(slope_o)) %>%
  mutate(road_sc = scale(road_o)) %>%
  mutate(dgrass100_sc = scale(dgrass100_o)) %>%
  mutate(asr_sc = scale(asr_o)) %>%

  # 9.2.2. Set reference level for habitat ####
mutate(habitat = factor(habitat,
                        levels = c(-63,1,6),
                        labels = c("bare", "grass", "timber"))) %>%
  mutate(habitat = relevel(habitat, ref = 'grass'))

head(dat)
str(dat)
table(dat$habitat)

# 9.3. Pre-scaling mean & SDs ####
mu_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_o <- dat %>%
  dplyr::summarise_at(vars(contains('_o')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')
```

```
params_o <- mu_o %>%
  full_join(sigma_o, by = 'covariate')

# Result
params_o

# Clean up
rm(mu_o, sigma_o)

# 9.4. Post-scaling means & SDs ####
mu_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

sigma_sc <- dat %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

params_sc <- mu_sc %>%
  full_join(sigma_sc, by = 'covariate')

# Result
# means should be about 0, and sd should be about 1 for all
params_sc

# Clean up
rm(mu_sc, sigma_sc)


#------------------------------------------------------------------------------#

# 10. - Scale covariate rasters ####

# 10.1. Subset raster stack to this season's layers ####
if(toggle %in% c('wd', 'wn')){asr_o = 'asrw_o'}
if(toggle %in% c('fd', 'fn')){asr_o = 'asrf_o'}
if(toggle %in% c('sd', 'sn')){asr_o = 'asrs_o'}
```

```
keep = c("habitat", "tpi_o", "slope_o", "road_o", "dgrass100_o","landsat_reclass")
rstack_season <- subset(rstack, subset = c(keep, asr_o))
names(rstack_season) <- c(keep, 'asr_o')

# 10.2. Scale continuous covariate rasters ####
# Scale all layers with names containing '_o'
# (omits 'habitat', leaving only continuous covariate layers)
params_o  # scaling parameters of points from section 9.3.
rstack_sc <- raster::scale(subset(rstack_season,
                                  subset = grep('_o',names(rstack_season)) ),
                           center = params_o$mu,
                           scale = params_o$sigma)

# Rename layers: replace _o with _sc
names(rstack_sc) <- gsub('_o', '_sc', names(rstack_sc))


# 10.3. Restack with habitat ####
rstack_sc <- raster::stack(raster::subset(rstack, subset='habitat'),
                           rstack_sc)

rstack_sc <- raster::stack(raster::subset(rstack, subset='landsat_reclass'),
                           rstack_sc)

# Result
rstack_sc
names(rstack_sc)
#plot(rstack_sc)

# 10.4. Post-scaling mu & sigma ####

# Means
rstack_mu_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), mean, na.rm = T) %>%
  dplyr::mutate(measure = 'mu') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# SDs
rstack_sigma_sc <- rstack_sc %>%
  as.data.frame() %>%
  dplyr::summarise_at(vars(contains('_sc')), sd, na.rm = T) %>%
```

```
  dplyr::mutate(measure = 'sigma') %>%
  tibble::column_to_rownames('measure') %>%
  t() %>%
  as.data.frame() %>%
  tibble::rownames_to_column('covariate')

# Join
rstack_param_sc <- rstack_mu_sc %>%
  full_join(rstack_sigma_sc, by = 'covariate')

# Result
rstack_param_sc

# Clean up
rm(rstack_mu_sc, rstack_sigma_sc)

# Compare
rstack_param_o      # pre-scaling mu & sigma
rstack_param_sc     # post-scaling mu & sigma for this season/daynight


#-------------------------------------------------------------------------#

# 11. Multicollinearity check ####

# 11.1 Input data ####
# Input data.frame from section 9.2.
head(dat)

# Format input data for analysis
glmerdat <- dat %>%
  dplyr::select(id = id,
                type = type,
                habitat = habitat,
                landsat_reclass = landsat_reclass,
                tpi = tpi_sc,
                slope = slope_sc,
                road = road_sc,
                dgrass100 = dgrass100_sc,
                asr = asr_sc)

str(glmerdat)

# change to factor and set ref level for landsat_reclass
levels(glmerdat$landsat_reclass)
glmerdat$landsat_reclass <- factor(glmerdat$landsat_reclass)
```

```
levels(glmerdat$landsat_reclass)
levels(glmerdat$landsat_reclass) <-
c("other","developed","barren","deciduous","evergreen",
                              "mixed","scrub","grass")
glmerdat$landsat_reclass <- relevel(glmerdat$landsat_reclass, ref = "grass")
str(glmerdat)
head(glmerdat)

w = table(glmerdat$landsat_reclass)
w



# Strip attributes for compatibility with newdat in section 13: predict
attributes(glmerdat$tpi) <- NULL
attributes(glmerdat$slope) <- NULL
attributes(glmerdat$road) <- NULL
attributes(glmerdat$dgrass100) <- NULL
attributes(glmerdat$asr) <- NULL

str(glmerdat)
head(glmerdat)

# 11.2. Scatterplot matrix  ####

# Choose title
if(toggle == 'wd'){m = 'Winter Day'}
if(toggle == 'wn'){m = 'Winter Night'}
if(toggle == 'fd'){m = 'Fall Day'}
if(toggle == 'fn'){m = 'Fall Night'}
if(toggle == 'sd'){m = 'Summer Day'}
if(toggle == 'sn'){m = 'Summer Night'}


# Visual check for multicolinearity
psych::pairs.panels(
  glmerdat[, c("habitat","landsat_reclass","tpi", "slope", "road", "dgrass100", "asr")],
  method = "pearson",
  hist.col = "#00AFBB",
  density = TRUE,
  ellipses = TRUE,
  main = m
)

# 11.3. VIF - wd ####
vif(
```

```
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
)

#------------------------------------------------------------------------#

# 12. Model Selection (AIC) ####

# 12.1. Base models ####

# 12.1.1. Null model ####

options(na.action = "na.fail")
nullmod <- glmer(type ~ 1 + (1|id), data = glmerdat, family = 'binomial')
summary(nullmod)

# 12.1.2. Full model ####

fullmod <-
  glmer(
    type ~ 1 + habitat + landsat_reclass + tpi + slope + road + dgrass100 + asr + (1|id),
    data = glmerdat,
    family = 'binomial'
  )
summary(fullmod)

# 12.2. Dredge ####
dredge(fullmod, beta = "sd", evaluate = TRUE)

# 12.3. Top model ####
#adjust based on dredge output!!!

refmod <-
  glmer(type ~ 1 + habitat + landsat_reclass + tpi + road + dgrass100 + (1|id),
        data = glmerdat,
        family = 'binomial')
summary(refmod)
#------------------------------------------------------------------------#

# 13. -- Predictions ####

# 13.1. Top model from Section 12 ####
# but without random effects
```

```
refmod.pred <-
  glm(type ~ habitat + tpi + dgrass100,
      data = glmerdat,
      family = 'binomial')
summary(refmod.pred)
class(refmod.pred)


# 13.2. Prep input data fopr predictions ####

# Scaled rasters for predictions
rstack_sc
names(rstack_sc)

# raster layers to keep
if(toggle == 'wd'){ss = c('habitat', 'tpi_sc', 'dgrass100_sc')}

newdat <- rstack_sc %>%
  # subset to raster layers we want to keep
  raster::subset(subset = ss) %>%
  # convert to data.frame
  as.data.frame() %>%
  # format habitat as factor
  mutate(habitat = factor(habitat_landcover,
                          levels = c("bare", "grass", "timber") )) %>%
  mutate(habitat = relevel(habitat, ref = 'grass')) %>%
  dplyr::select(-c(habitat_COUNT, habitat_landcover)) %>%  #edit - added dplyr::select
here
  # remove _sc extensions on column names
  dplyr::rename_all(gsub, pattern = '*_sc$', replacement = '')

head(newdat)
str(newdat)


# 13.3. Predict - nonspatial ####
?predict.glm
newdat$pred.logit <- stats::predict(refmod.pred,
                                    newdata = newdat,
                                    level = 0)

head(newdat)
str(newdat)

# 13.4. Back-transform predicted values ####
library(boot)
```

```
?inv.logit
newdat$pred <- inv.logit(newdat$pred.logit)
head(newdat)

# 13.5. Promote predictions to spatial ####
pred.ras <- rstack_sc$habitat # template
pred.ras[] <- newdat$pred # fill in values
plot(pred.ras, main = m)

# 13.6. Plot with MCP & points ####
mcp = readOGR(dsn = getwd(),
              layer = paste0(toggle,'_mcp90'),
              stringsAsFactors = F)

plot(pred.ras, main = paste('Probability of elk & 90% MCP HR:', m) )
plot(mcp,border = 'black',add =T)
plot(ap[ap$type == 1,], add = T, pch = 20, cex = 0.01)

# 13.7. Save prediction raster to file ####
writeRaster(pred.ras, filename = paste0(toggle,'_pred.tif'))
```

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